REPORT DOCUMENTATION PAGE

1. REPORT DATE (dd-mm-yy) February 1991	2. REPORT TYPE Final	3. DATES COVERED (from... to) Oct 88 – Sep 90

4. TITLE AND SUBTITLE Military Compensation and Personnel Retention: Models and Evidence	5a. CONTRACT OR GRANT NUMBER 5b. PROGRAM ELEMENT NUMBER
6. AUTHOR(S) Gilroy, Curtis L.; Horne, David K; and Smith, D. Alton	5c. PROJECT NUMBER 5d. TASK NUMBER 5e. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) U.S. Army Research Institute for the Behavioral and Social Sciences 5001 Eisenhower Avenue Alexandria, VA 22333-5600	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) U.S. Army Research Institute for the Behavioral and Social Sciences 5001 Eisenhower Avenue Alexandria, VA 22333-5600	10. MONITOR ACRONYM ARI 11. MONITOR REPORT NUMBER

12. DISTRIBUTION/AVAILABILITY STATEMENT

Approved for public release; distribution is unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT *(Maximum 200 words)*:

This book deals with both theoretical and empirical economic literature on labor supply, and provides the Army with the basis upon which to improve the management of enlisted retention. It brings together a collection of research papers that provide quantitatively defensible formulations of the influence of military pay, bonuses, retirement benefits, and other factors on enlisted retention.

15. SUBJECT TERMS

Military Compensation; Retention; Labor Supply

SECURITY CLASSIFICATION OF			19. LIMITATION OF ABSTRACT	20. NUMBER OF PAGES	21. RESPONSIBLE PERSON (Name and Telephone Number)
16. REPORT Unclassified	17. ABSTRACT Unclassified	18. THIS PAGE Unclassified	Unlimited	416	David W. Witter (703) 617-0324

Military Compensation and Personnel Retention

Models and Evidence

Edited by

Curtis L. Gilroy
David K. Horne
D. Alton Smith

United States Army Research Institute
for the Behavioral and Social Sciences

February 1991

U.S. Army Research Institute for
the Behavioral and Social Sciences
Alexandria, Virginia

Editors

Dr. Curtis L. Gilroy is currently Chief, Manpower and Personnel Policy Research Group, U.S. Army Research Institute. Prior to this appointment, Dr. Gilroy served as a senior staff economist with the Minimum Wage Study Commission and the National Commission on Employment and Unemployment Statistics. He has been a research economist with the Bureau of Labor Statistics, U.S. Department of Labor, and has taught economics at the college level. Dr. Gilroy obtained an M.A. from the University of Toronto, an M.B.A. from McMaster University, and his Ph.D. in economics from the State University of New York, Binghamton.

Dr. David K. Horne is an economist with the Federal Deposit Insurance Corporation, Research and Statistics Division. He participated in this project in his previous position at the U.S. Army Research Institute. Dr. Horne obtained his B.A. from Bates College and his Ph.D. in economics from the University of Pennsylvania.

Dr. D. Alton Smith is Deputy Director of the Economics and Management Systems Division of Systems Research and Applications Corporation in Arlington, Virginia. His prior positions include visiting professor at the U.S. Military Academy, West Point, and senior economist at Abt Associates in Cambridge, Massachusetts. Dr. Smith obtained his A.B. from Princeton University and his Ph.D. in economics from the Massachusetts Institute of Technology.

Contents

Preface

The research presented in this volume is at the cutting edge of the theoretical and empirical economic literature on labor supply, and provides the U.S. Army with the basis upon which to make significant decisions to improve the management of enlisted retention. The role of compensation and other factors in the individual reenlistment decision has been the topic of considerable interest and research. In this volume we have brought together a collection of research papers that provides quantitatively defensible formulations of the influence of military pay, bonuses, retirement benefits, and other factors on enlisted retention.

This research was funded by the U.S. Army Research Institute (ARI), and was a two-year effort conceived by myself and Dr. David Horne of the Manpower and Personnel Policy Research Group, ARI. We were responsible for both the monitoring and the technical review of the research for the U.S. Army. Dr. D. Alton Smith of Systems Research and Applications Corporation was the principal investigator and coordinated the research.

This volume not only demonstrates the quality of economic research currently undertaken in the military, especially the U.S. Army, but is a tribute to the Deputy Chief of Staff for Personnel for supporting, fostering, and using research such as this for the formulation of Army manpower policy. Lieutenant General Allen K. Ono has been supportive of my research program for many years, and I am particularly grateful to him. Dr. Edgar Johnson, Technical Director of the U.S. Army Research Institute, and COL Jon Blades, Commander, have provided continual support and encouragement of my program at the Institute.

I am also extremely grateful to Ms. Kathryn Fowler, Chief, Publications Office, ARI, for her assistance and enthusiasm in preparing this manuscript for publication.

CURTIS L. GILROY

Contributors

Matthew Black	Systems Research and Applications Corporation
Charles Brown	University of Michigan *and* National Bureau of Economic Research
Thomas V. Daula	United States Military Academy
Curtis L. Gilroy	United States Army Research Institute
Matthew S. Goldberg	Institute for Defense Analyses
Paul F. Hogan	Decision Science Consortium, Incorporated
David K. Horne	Federal Deposit Insurance Corporation
Robert A. Moffitt	Brown University *and* New York University
Roy D. Nord	United States Army Research Institute
Walter Y. Oi	University of Rochester
Sherwin Rosen	University of Chicago
D. Alton Smith	Systems Research and Applications Corporation
Gary Solon	University of Michigan
Frank P. Stafford	University of Michigan
Stephen D. Sylwester	Systems Research and Applications Corporation
John T. Warner	Clemson University
Christine M. Villa	Systems Research and Applications Corporation
David A. Wise	Harvard University *and* National Bureau of Economic Research

1

Introduction

David K. Horne
Curtis L. Gilroy

I. Overview

This volume contains a collection of papers addressing the role of compensation in military retention. The military services require large numbers of personnel to meet manpower requirements each year, and the demand is met both by attracting a large number of recruits at the entry level, and by retaining a sufficient number of soldiers to meet the requirements at higher ranks. The major policy tool used to attract and retain these personnel is compensation. A quantitative understanding of how compensation affects reenlistment decisions is an important input to both manpower planning and policy evaluation.

The Army is one of the largest employers in the world, with 685,300 active duty enlisted personnel and 106,900 active duty officers, supplemented by a 457,000 National Guard force and 319,200 Selected Reserves at the end of fiscal year (FY) 1989. The Military Personnel budget, at $30 billion in 1990, accounts for 38 percent of the total Army budget. Substantial recruiting and retention incentives, including various forms of compensation, are necessary to maintain the flows of personnel to support these requirements. The magnitude of the Army personnel system suggests that small improvements in the efficient use of compensation may have substantial dollar benefits.

Army manpower requirements, as in the private sector, are defined by skills, grades, and the "quality" of personnel. For

the enlisted force, there are some 350 different skills, or military occupational specialties. Individuals are normally recruited into and trained for particular specialties, conditional upon meeting minimum qualifying test scores that are defined for each specialty. After basic and advanced individual training, soldiers are sent to the field to receive specific on-the-job training. Upon completing their first term, soldiers may have the option of reenlisting for additional tours. Promotion rates vary across occupational specialties. Normally, individuals enlist at a pay grade of E1 or E2, reach E3 upon completing training, and progress over time up to a maximum pay grade of E9 depending upon the number of vacancies and the number of soldiers eligible for promotion.

Army retention is one mechanism to meet overall manpower requirements, as well as to achieve the appropriate personnel distribution across jobs and levels of experience. The research in this volume focuses on retention behavior of the enlisted force, particularly at the first and second reenlistment points. The primary emphasis of this research is to develop a methodological framework to estimate the effects of compensation and other factors on the individual retention decision. This overview is intended to provide a brief introduction to the institutional framework in which retention decisions are made and to illustrate some of the methodological issues addressed in the retention literature. Some understanding of Army personnel policies may be useful for interpreting the implications of the research presented in this volume. The institutional framework is presented in Section II, while the purpose of the research and brief summaries of the papers are provided in Section III.

II. Institutional Framework

The Army normally recruits individuals for tours of two to four years (or up to six years in a limited number of specialties). Individuals sign enlistment contracts that obligate them to enter active service on a particular date, and to complete a tour of specified length. However, there are losses throughout the enlistment process. Over 10 percent of individuals who sign an enlistment contract never actually access onto active duty. Of those who do enlist, nearly 30 percent do not complete their first tour. Soldiers who do complete their first term have the

option of reenlisting if they meet eligibility requirements. Eligibility is a function of a number of factors such as commander evaluations, scores on Army job performance and aptitude tests, and physical standards. Some of these factors act as absolute bars to reenlistment, but others can be overcome either by soldiers themselves (e.g., by retaking the aptitude test) or by their supervisors (by issuing waivers). In 1989, 39,500 soldiers reenlisted upon completion of their first tour (see Table 1.1).

Table 1.1
Reenlistments, FY 1989 and FY 1990
(in thousands)

	FY 1989			FY 1990
Term	**Goal**	**Actual**	**Percent**	**Goal**
Initial Term	34.4	39.5	115.8	31.4
Mid-Career	25.4	32.3	127.2	22.0
Career	28.2	30.4	107.8	25.0
TOTAL	88.0	102.2	116.2	78.4

Source: Manpower Requirements Report FY 1991 (1990).

Historically, the Army has used eligibility requirements to influence the quality of soldiers who reenlist. Current Army regulations (AR 601-208, 8 June 1988), for example, require meeting eligibility criteria in such areas as suitability and basic qualifications, age, citizenship, trainability, education, medical and physical fitness, moral record, time-in-service and grade, and skill qualifications. Soldiers must obtain minimum scores on various combinations of subtests of the Armed Services Vocational Aptitude Battery (ASVAB),[1] must achieve a passing score on their most recent Skill Qualifications Test,[2] and must possess a high school diploma, GED (Graduate Equivalency Diploma) or Associates or higher degree. The eligibility criteria complicate modeling the retention behavior of Army personnel, as the policies are not only difficult to quantify, but frequently change. At the individual level, eligibility ratings cannot be considered

given (or exogenous) because they can often be altered by actions of the soldier.

Retention rates vary significantly across tours. Approximately 30 to 40 percent of those who complete their initial term of service reenlist, but reenlistment rates increase after the first term; between 50 and 60 percent reenlist at completion of the second tour. Reenlistment rates jump dramatically at later reenlistment points, largely because of the attractive vesting provisions of the military retirement program. In addition, reenlistment rates also rise because the average preference or "taste" for military service increases with years of service as individuals with lower preferences select themselves out of military careers. Because reenlistment rates after the third enlistment tour are quite close to unity and are relatively insensitive to personnel policies, they are not investigated in this effort.

The Army requires substantial numbers of reenlistees in order to maintain a desired force structure. There is some tradeoff between retention and enlistments that can be made in order to maintain a constant overall force size (end-strength), although the physical demands of Army service require a substantial number of youthful recruits each year. Where the Army has some flexibility, the relative costs of recruiting versus retention should play a role in determining the most effective use of scarce resources. In skills where it is less expensive to retain a soldier, other things equal, higher retention rates should be maintained due to the costs of recruiting and training soldiers. Conversely, it is logical to expect that when recruiting becomes more difficult, retention should increase (insofar as the Army can influence retention) to offset enlistment shortfalls.

The Army has a variety of policies that can be used to influence personnel retention. This volume focuses on compensation, because it directly affects personnel supply. The most straightforward and visible measure of compensation is basic pay, the pay structure being identical for all services; basic pay is primarily a function of longevity and grade as seen from the 1990 pay table provided in Table 1.2. Other benefits, such as allowances for quarters and subsistence (food) are a function of grade, but vary as well on the basis of marital status and number of dependents. The Army, like the other services, has some influence over these components, but has limited control in the short run

Table 1.2
Enlisted Members Basic Pay

Pay Grade	Years of Service: less than 2	2	3	4	6	8	10	12	14	16	18	20	22	26
E-1	*(less than 4 months)*			669.60										
E-1	724.20	724.20	724.20	724.20	724.20	724.20	724.20	724.20	724.20	724.20	724.20	724.20	724.20	724.20
E-2	811.80	811.80	811.80	811.80	811.80	811.80	811.80	811.80	811.80	811.80	811.80	811.80	811.80	811.80
E-3	843.60	889.80	925.50	962.10	962.10	962.10	962.10	962.10	962.10	962.10	962.10	962.10	962.10	962.10
E-4	895.50	945.60	1001.10	1078.80	1121.40	1121.40	1121.40	1121.40	1121.40	1121.40	1121.40	1121.40	1121.40	1121.40
E-5	960.00	1044.90	1095.60	1143.30	1218.30	1268.10	1318.50	1366.80	1391.70	1391.70	1391.70	1391.70	1391.70	1391.70
E-6	1094.10	1192.20	1242.00	1294.80	1343.10	1391.70	1443.00	1517.40	1564.80	1615.50	1640.10	1640.10	1640.10	1640.10
E-7	1271.40	1372.50	1423.50	1473.30	1523.40	1572.00	1622.40	1672.40	1748.70	1798.20	1848.30	1872.30	1998.00	2246.70
E-8	0.00	0.00	0.00	0.00	0.00	1821.30	1873.20	1922.70	1972.50	2024.70	2071.20	2122.20	2246.70	2496.90
E-9	0.00	0.00	0.00	0.00	0.00	0.00	2171.70	2220.60	2271.00	2322.90	2374.80	2421.00	2548.20	2796.00

Basic Allowance for Quarters (BAQ)

	Dependents: Without, Full	Without, Partial	With
E-1	155.70	6.90	278.40
E-2	175.20	7.20	278.40
E-3	215.70	7.80	292.50
E-4	219.60	8.10	314.40
E-5	252.30	8.70	361.50
E-6	273.60	9.90	402.00
E-7	302.40	12.00	435.30
E-8	354.30	15.30	468.30
E-9	385.50	18.60	508.20

Basic Allowance for Subsistence

Enlisted Members

When on leave or authorized to mess separately	$5.91/day
When rations in-kind are not available	$6.67/day
When assigned to duty under emergency conditions where no messing facilities of the United States are available	$8.84/day

(only the President and the Congress can approve a pay increase). However, the Army can influence promotions, which affect the seniority of the force and, in turn, total compensation.

Other components of the pay package, such as special pays for hazardous duty, are relatively small expenditures in comparison with basic pay, and are not designed to have a large impact on overall retention. Retirement benefits, on the other hand, have a major impact on retention behavior, particularly in later tours. Unlike private sector plans, soldier vesting is zero before 20 years of service and 100 percent thereafter. Soldiers may collect retirement benefits at separation (equal to 2.5 percent times years of service, although slightly different benefits apply to soldiers enlisting after 1980). The Army is charged 51 percent of each soldier's basic pay to finance retirement costs.[3]

Reenlistment bonuses are another component of the compensation package, and are the major retention policy tool available to policymakers. The allocation of selective reenlistment bonuses is carefully managed; bonus levels are increased or decreased, and occupational specialties may be added or dropped from bonus eligibility in order to fill manpower requirements. Reenlistment bonuses are specified in terms of levels, which range from 1 to 5 based on the criticality and projected shortages associated with the specialty. The total value of the reenlistment bonus to an individual soldier is calculated as a multiple of the bonus level times the number of years of the reenlistment commitment times the soldier's current pay. This arrangement provides an incentive for longer reenlistment commitments. The Army has authority to offer reenlistment bonuses up to $45,000, although only 10 percent of all bonuses can exceed $20,000. The Army currently, however, does not award any reenlistment bonus in excess of $20,000. Soldiers can choose to receive their bonus in equal installments over the tour, or may opt to receive 50 percent of the amount in a lump sum with the remainder to be paid in equal installments.

The primary purpose of reenlistment bonuses is to serve as an incentive for soldiers to reenlist in critical or hard-to-fill occupational specialties. The nature of the bonus program, therefore, makes it inappropriate to estimate the effects of bonuses from cross-sectional data, because the existing bonus

reflects both demand and supply conditions. Much of the research in this volume uses a longitudinal data set assembled specifically to analyze retention behavior (Nosnisky et al., 1990). Trends in selective reenlistment bonuses over time are illustrated in Table 1.3. Although the Army has control over the allocation of bonus dollars, the total reenlistment bonus budget has been limited by both the Office of the Secretary of Defense (OSD) and the Congress. Selective reenlistment bonuses are currently available to only about one third of all occupational specialties in the Army, and approximately 15 percent of all soldiers reenlisting qualify for bonuses. The selective reenlistment bonus budget is currently about $90 million (Table 1.3).

Table 1.3
Army Selective Reenlistment Bonus Budget, FY 1986–91

Fiscal Year	Budget (in $ millions)
1986	140.4
1987	110.0
1988	99.5
1989	115.1
1990	99.0
1991	88.4

Source: U.S. Army Office of the Deputy Chief of Staff for Personnel.

The Army, then, has a number of policy tools available to influence retention, such as basic pay (established for all services), bonuses, promotion policies, and retirement benefits. With the exception of bonus allocation and promotion policies, the Army has direct control over relatively few of these. But even the bonus budget is subject to Congressional approval, and promotion time is not easy to manipulate, being largely driven by supply; in the least popular skills, higher turnover will create more advancement opportunities, and thus shorter promotion times.

III. Purpose of This Research

Economic research has played a vital role in formulating manpower policy in the All-Volunteer Force (AVF) era. The termination of the draft in 1973 brought compensation, in particular, to the forefront of defense manpower policy. In fact, compensation is the largest component of defense costs.[4] No longer is it viewed simply as a reward for service; rather it is now used as a policy tool for managing the military manpower and personnel system. Indeed, compensation policy is the single most important element of manpower policy with respect to influencing labor supply behavior, i.e., recruitment and reenlistment (Cooper, 1977). With the advent of the AVF, market forces—and how the Army responds to them—shape what the force will look like.

Military compensation to a limited degree had been used as a policy tool in the pre-AVF era. Shifting manpower supply and demand conditions required that some changes in the system be instituted even under the draft. The introduction of proficiency pay in the late 1950s and the variable reenlistment bonus program in 1966—both instituted to alleviate chronic manpower shortages in highly technical enlisted occupational specialties—are examples of the military's response to market phenomena. The first two of a series of Quadrennial Reviews of Military Compensation in 1967 and 1971, as well as seven other major studies of military manpower in the post-World War II period, examined the role and impact of military compensation on manpower supply and personnel allocation in the pre-AVF era.

Perhaps the most important of these studies was the Report of the President's Commission on an All-Volunteer Force (1970)—popularly referred to as the Gates Commission—which stressed the importance of compensation in recruiting and retaining an all-volunteer force. The Commission recognized the special problems that the Army was likely to face because

> "... the non-monetary conditions of service are less attractive in the Army than in the other three services" (Report, p. 56).

The Commission recommended increases in basic pay,

> ". . . to provide the Army with the quantity and quality of volunteers required for an overall force level of 2.5 million men. The evidence is overwhelming that, if compensation is set to levels which satisfy Army requirements, the other services will be able to attract enough qualified volunteers to meet their respective requirements" (Report, p. 57).

In addition, special pays were recommended as compensating wage differentials. Proficiency pay for persons with special skills and hostile-fire pay for hazardous combat duty were singled out as specific examples.

For sound policy formulation, policymakers must determine the manpower requirements needed to carry out the Army's mission. They must then examine the incentive structure, including each of the components of the Army's compensation package, to determine the most effective means of meeting personnel requirements. In order to do this, however, the impact of each component must be quantified. To determine the size of the effect that a compensation change such as an increase in the selective reenlistment bonus (SRB) may have on retention, requires information about the manpower supply curve. The size of the reenlistment bonus required to increase the supply of soldiers into a particular occupational specialty would depend upon the elasticity (slope) of the supply curve for that specialty. For example, in order to increase the supply from F_0 to F_1 in Figure 1.1, a larger bonus (B_2) would be required if the supply curve were relatively inelastic (SS) than the bonus required (B_1) if the curve were relatively elastic (S′S′).

For each occupational specialty, then, the level of compensation will reflect demand and supply conditions for soldiers. In equilibrium (for example, point X in Figure 1.1 corresponding to bonus B_2 and supply F_1) the bonus is high enough to retain just the amount demanded by the Army in that specialty denoted by supply curve SS. If the bonus is too low (B_0), the number of soldiers who reenlist will be less than the number desired, and a shortfall amounting to F_0F_1 will result. The shortfall can be eliminated by raising the bonus level. If resources are constrained, however, the Army must optimize over all specialties to determine what levels of shortages are to

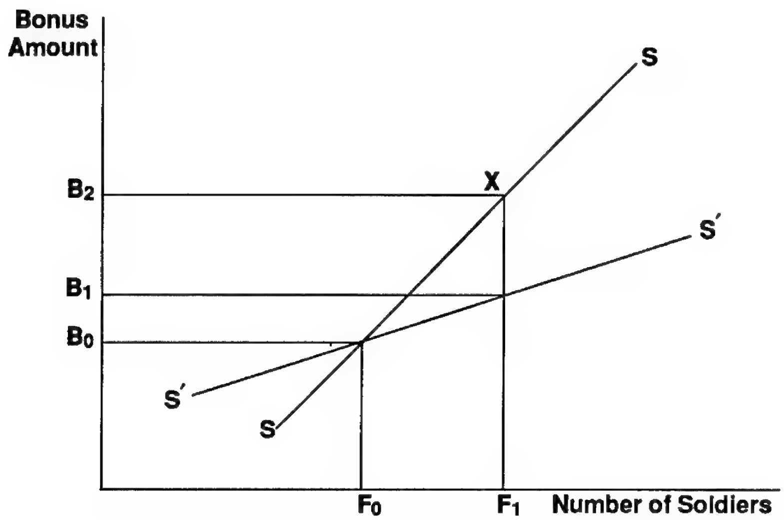

Figure 1.1 Reenlistment Supply

exist in which skill. If policymakers do not know what the skill-specific supply curves look like, the Army will be unable to even settle on a "reasonable" solution.

Effective management of compensation, then, requires knowledge of the impact of military compensation on retention. The optimal size of the pay package and the allocation of the budget across occupational specialties cannot be determined without information on the effect of compensation on labor supply. Accurate estimates of the effects of such policy variables as bonuses, pay, and retirement benefits are necessary for efficient personnel management. Issues requiring such information include: (a) filling positions by recruitment versus retention, (b) determining the cost-effectiveness of paying selective reenlistment bonuses, (c) allocating a fixed selective reenlistment bonus budget among occupational specialties, (d) simulating the effects of alternative personnel policies (such as time to promotion) on retention, and (e) deriving least-cost solutions of reaching enlisted force-structure objectives. The Army presently does not have accurate information on the

retention impact of various personnel policies, a situation that creates difficulties in designing efficient compensation policies.

Without theoretically and empirically defensible formulations, estimates of pay elasticities, bonus effects, or the impact of other policy changes will be suspect. The papers in this volume investigate a variety of retention issues that center specifically on Army enlisted personnel. The research focus of each of these papers is briefly summarized below.

Chapter 2 reviews the existing literature on economic models of retention, focusing on the key methodological issues that have been addressed in the research. Hogan and Black discuss the development of the Annualized Cost of Leaving (ACOL) models, the most commonly used approach to modeling the reenlistment decision, and compare it to the more sophisticated dynamic reenlistment models. Both the ACOL and dynamic reenlistment models are based upon a comparison of military and civilian compensation streams, but the approaches differ in how the comparison is made. A number of additional methodological issues such as compensating wage differentials, personal discount rates, post-service earnings data, risk, optimal decision rules, and expectations are also discussed by Hogan and Black.

Chapter 3 provides a baseline for the following chapters. The purpose of the research in this chapter is to use state-of-the-art statistical techniques involving dynamic retention models, apply these models to the best data available, estimate the models across a variety of occupational specialties, and test the sensitivity of the results over a number of different specifications. Subsequent chapters extend the frontier in a number of different ways, comparing the results with the baseline estimates here.

In this chapter, Smith, Sylwester, and Villa use a dynamic version of the ACOL approach, called the ACOL-2 model. An individual-specific component is introduced into the reenlistment model to account for unobserved factors at the second reenlistment point that are not independent of the retention decisions made at the first reenlistment point. Specifically, individuals who face the second reenlistment decision are likely to have relatively stronger "tastes" for military service than the sample at the first reenlistment point, as those with

lower preferences for service are more likely to have left after completing their first tour. A reenlistment choice model is estimated jointly for the first and second reenlistment decisions for three career management fields: Infantry, Mechanical Maintenance, and Administration.

To construct the ACOL variable, Smith, Sylwester, and Villa estimate both (1) expected military earnings, using time-to-promotion models that are a function of soldier characteristics, and (2) the civilian earnings that would be expected if the soldier left the Army. The estimated ACOL values are input into the reenlistment models. Post-service earnings are predicted from models estimated with the Post-Service Earnings History File, which combines Army personnel files with earnings data from the Internal Revenue Service. Post-service earnings are found to increase with both military and civilian work experience, although at a declining rate. These earnings are relatively lower in the first year of separation, attributed to transitional unemployment or part-time work due to the pursuit of additional education. Other determinants of post-service earnings include such factors as education, AFQT score, military performance, gender, and unemployment.

The major results of policy interest from the retention equations involve the pay elasticities (the percentage change in retention associated with a given percentage change in pay). For example, the elasticity of the reenlistment rate with respect to a *pay* increase is estimated to be 1.3 for first-term soldiers in Infantry specialties and 0.9 for those at the second reenlistment point. A one-level increase in the *selective reenlistment bonus* increases first-term reenlistment rates by 2.2 percent and second-term reenlistment by 1.7 percent in Infantry. Reenlistment rates were more sensitive to compensation (i.e., higher pay elasticities) in more technical specialties. For example, the pay elasticity for first-term soldiers was 1.8 in Mechanical Maintenance and 1.9 for soldiers in Administration. These findings are useful from a policy perspective, of course, but another major contribution of this chapter should not be overlooked. A number of methodological issues are raised, and various model assumptions are investigated in order to measure the sensitivity of the empirical estimates. Issues addressed include migration to different occupational

specialties at reenlistment, the impact of ways to treat eligibility criteria, and alternative models of how expectations of future earnings are formed.

Chapter 4 addresses the dynamic nature of retention models. The relative cost of separating from the military is a function of the expected length of a military career. For example, different costs will be generated if the cost of one additional year of service is compared with the cost of remaining in the Army until eligible for retirement benefits (after 20 years of service). Moreover, the choice of time horizon has implications for evaluating particular policies. For example, if a short horizon is assumed, changes in the retirement program will, by definition, have no impact on retention. The appropriate choice of a horizon is, therefore, critical to obtaining accurate estimates of the impact of certain policy changes.

The ACOL model has a somewhat simplistic way to determine the appropriate career horizon. Daula and Moffitt develop a method for estimating a dynamic programming model with a more realistic treatment of the horizon-choice problem and, just as importantly, demonstrate a method for estimating the parameters of the model. The procedure is iterative, first using the predicted retention rates to generate the values of relative military-civilian compensation. These values are then used to generate a new set of retention probabilities across different horizons, and these probabilities are subsequently used to create the next relative compensation estimates. The dynamic programming model fits better than the ACOL and probit models tested, but it demonstrates similar effects of policy initiatives, such as pay changes. The pay elasticity for Infantry is estimated to be 1.2, slightly less than the estimate derived by Smith, Sylwester, and Villa in Chapter 3.

In Chapter 5, Brown provides a model of retention that focuses on the role of personnel quality. Quality indicators such as AFQT score, education, pay grade, and job performance test measures are all likely to be associated with performance, and it is in the Army's best interest to retain soldiers who demonstrate higher levels of job performance. Army compensation appears to be less sensitive to performance than civilian pay, which suggests that the costs of leaving the Army are less for higher quality personnel. However, because the Army can

set eligibility standards on the basis of these quality indicators, better soldiers are more likely to meet eligibility criteria. To quantify the personnel quality effect, Brown incorporates both the reenlistment decision (as a function of the quality indicators) and Army screening (on the basis of eligibility criteria) explicitly in a two-equation model. Brown finds that those with high school diplomas and higher Skill Qualification Test (SQT) scores are more likely to meet eligibility criteria. Ineligibility rates for the sample are relatively small. Therefore, eligibility screening has a small positive effect on the remaining sample. After accounting for eligibility criteria, higher SQT scores are associated with higher reenlistment probabilities, but individuals with higher AFQT scores have lower retention rates.

Chapter 6 investigates how sample selectivity due to first-term attrition affects retention models. Enlistment and attrition of cohorts may have an impact on the relationship between compensation and reenlistment because both affect the average “taste” for military service of the soldiers reaching the reenlistment point. If there is a correlation between the errors in the attrition and reenlistment equations, the reenlistment parameters may be sensitive to variations in enlistment and attrition patterns over time. Warner and Solon investigate this potential problem by estimating a joint model of attrition and reenlistment. The research compares several models to analyze first-term attrition and reenlistment, including probit, logit, and proportional hazard models. The results of the joint attrition and reenlistment model suggest that the standard procedure of ignoring attrition does not introduce serious biases into the reenlistment model when a rich set of regressors is used. Conditions at the time of the initial enlistment do have an impact on reenlistment even after controlling for conditions at the time of reenlistment.

A framework for designing an optimal compensation system to meet the requirements of manning the force at a minimum cost is provided by Stafford in Chapter 7. Military service is modeled as a partial career in which the Army offers training and compensation for a commitment of a given length of time. Individuals enter the Army because of the training offered but, having acquired new skills, become more difficult to retain

because of their increased civilian earnings potential. This suggests that military compensation should vary by occupation if the value of military training in terms of post-service earnings also varies by occupation. To investigate this issue, Stafford estimates post-service earnings models across different occupational specialties, and finds significant variation in the returns to military experience. Army service has a positive impact on subsequent earnings in the civilian labor market. For example, civilian earnings increase at a rate of 5 to 6 percent per year of military service. The shape of the civilian earnings profile varies across occupational specialties because some specialties provide greater incentives to leave. The practical implication is that it would be useful for the Army to target compensation to overcome differential returns to service.

The attrition and reenlistment effects of a special enlistment incentive—the Army College Fund (ACF)—are examined in Chapter 8. The ACF provides educational benefits over and above the basic military Montgomery GI Bill program, and is offered to high-quality recruits who enlist in particular occupational specialties. The cost-effectiveness of the ACF has been difficult to quantify in the past because relatively little has been known about the effects of the program on attrition and retention. The authors find no statistically significant impact of ACF on attrition, although they find a small negative effect on reenlistment. An educational benefit usage rate equation is estimated, correcting for censoring in the data due to the relatively short usage period observed for current ACF benefit programs. ACF eligibility is associated with greater use of educational benefits, as is AFQT score, educational attainment, and several other variables. Due to the negative impact on retention, the ACF is most cost-effective where training costs are relatively low, and in such cases may be more cost-effective than enlistment bonuses in these specialties. However, for a more precise assessment, more usage data must be observed.

Retention in the Army Reserves is the topic of Chapter 9. Reserves have played an increasing role in national defense in recent years, but the retention of reservists and the role of compensation has received relatively little attention. Hogan and Villa analyze personnel files that have been merged with

1986 survey data. They find that reserve pay appears to have a significant effect on retention for those with six years or less of service. Approximately 1.3 percent of reservists are retained with a 10 percent increase in pay. However, the authors caution that the relatively low response rates and the use of cross-sectional data may create estimation problems. Therefore, the empirical results should be accepted with some skepticism, as data limitations continue to plague the study of reserve retention. Given the importance of reserve forces in current defense strategies and the size of the reserve personnel requirements, improvements in data may yield large payoffs in the future.

This volume contains research that addresses issues in building theoretically and empirically defensible retention models, as well as providing useful information on the determinants of the reenlistment decisions of enlisted personnel. Such information is likely to be particularly relevant in the near future as policy decisions are made about how to reduce the enlisted force and alter the personnel structure of not only the Army, but the other services as well, in light of rapidly changing political events in Eastern Europe and concerns about the large domestic budget deficit. Total compensation, promotions, bonuses, and other policy instruments are likely to change given the planned reductions in personnel. Improved estimates of the effects of these factors on retention will allow the services to more accurately manage retention to meet end-strength goals in a cost-effective manner.[5]

Notes

1. The Armed Services Vocational Aptitude Battery (ASVAB) is a collection of 10 written subtests administered to all youth before they enlist, measuring aptitude in arithmetic reasoning, mathematical knowledge, paragraph comprehension, word knowledge, auto shop knowledge, coding speed, electronics, general science, mechanical comprehension, and numerical operations. The first four subtests comprise the special Armed Forces Qualification Test (AFQT) composite, a measure of soldier ability or "quality" used to predict overall success in the military.

2. The Skill Qualifications Tests are administered on an annual basis to soldiers in most occupational specialties. These tests are designed to measure proficiency on a variety of tasks, at each of four skill levels associated with different pay grades.

3. This percentage is applied by the Department of Defense to all services, although the Army's true retirement costs are lower due to lower retention rates relative to the other services, as discussed in Hogan and Horne (1990).

4. The Army Military Personnel budget exceeds the totals for Operations and Maintenance, Procurement, and other appropriations categories.

5. ARI is currently developing the Enlisted Personnel Inventory Cost and Compensation (EPICC) model to integrate the retention estimates derived from this research into an inventory model, which will also incorporate cost data from the Army Manpower Cost System (AMCOS). The effect of compensation policies would directly influence the transition rates in the inventory model, so different compensation policies designed to meet end-strength objectives could be compared directly.

2

Reenlistment Models: A Methodological Review

Paul F. Hogan
Matthew Black

I. Introduction

The reenlistment decision—the decision to remain in or leave military service—is a particular application of the more general economic theory of occupational choice, which dates back to Adam Smith (1776). The premise common to the economic literature concerned with occupational choice is that rational individuals choose among alternative occupations based upon the pecuniary and nonpecuniary attributes of each alternative, such as current pay, deferred pay, hours of work, location, and physical risk. The individual acts as if he ranks alternatives in terms of the expected satisfaction these attributes provide. He chooses the alternative occupation, or path of occupations, that offers the greatest satisfaction or utility over his lifetime.

Models of the decision to remain in or leave military service have importance beyond the intellectual exercise of economic theory and practice. Reenlistment models have been used to help formulate policy on annual military pay raises, reenlistment bonuses, and changes in the military retirement system. The advent of the volunteer force in 1973 was influenced, in part, by predictions of the increases in retention that could be anticipated under alternative pay policies. Hence, the degree

of rigor with which these models are specified and estimated, and the accuracy with which they predict the effects of alternative policies, are of no small concern. The costs of inaccurate predictions, in many instances, are too large to dismiss casually.

The emphasis of this literature review is primarily methodological. We do not review and compare specific empirical results in any great detail. Rather, we trace the progress of researchers in specifying increasingly rich theoretical models and in estimating models consistent with this theoretical structure. Our goal is to provide for the reader the methodological context for the original papers that follow in this volume.

Section II provides a brief overview of reenlistment decision models. Section III outlines early reenlistment behavior research. Section IV describes the historical development of the Annualized Cost of Leaving, or ACOL, model, which has been the most frequently used framework for analyzing reenlistment decisions. Section V describes the major theoretical shortcomings of the ACOL model and introduces the dynamic retention models that have been developed in an attempt to address those problems. In Section VI we identify other methodological issues that arise in reenlistment research, such as obtaining consistent estimates of post-service earnings and choosing an appropriate discount rate.

II. Overview of Reenlistment Decision Models

With few exceptions, the underlying theoretical structure of reenlistment decision models has remained firmly grounded in the economic theory of occupational choice. However, much progress has been made in modeling reenlistment behavior over the past 15 years. This progress has occurred primarily in four areas: (1) the extent to which institutional details are captured in the models, (2) the sophistication of econometric methods used in estimating the models, (3) the greater correspondence between the underlying theory and the econometric specification, and (4) the adaptability of relatively sophisticated retention models for use in easily operated policy simulation models.

The following review is organized into three major sections and corresponds roughly to the intellectual development of

reenlistment models. The first section, described as the "early work," began around the time of the Gates Commission in 1970 (formally referred to as the *Report of the President's Commission on an All-Volunteer Force*) and continued through the late 1970's. The impetus to this work was largely to obtain estimates of the effects of extant policy variables, such as pay and bonuses, so that the effects of increasing or decreasing these incentives could be evaluated for policy purposes. This research concentrated almost exclusively on the reenlistment decision occurring at the end of the first term of service and was characterized by *ad hoc* model specifications and limited data.

The second period began with the development and application of the Annualized Cost of Leaving (ACOL) model. It is characterized by: (1) concern with the ability of a model to simulate the effects of relatively large changes in policies, such as the military retirement system, (2) increasing attention paid to the relationship between the estimated model and its underlying theory of optimal decision making, and (3) recognition of the institutional constraints placed upon service members. Some analysis in this period expanded beyond the first-term decision to encompass a multidecision framework.

The last period can be described as the post-ACOL era. Emphasis is placed on extending the ACOL methodology with dynamic retention models of individual decision making over time, and on the economic interpretation and modeling of complex error structures.

As an example, consider the evolution in estimating the effect of reenlistment bonuses. In some early work (e.g., Enns 1977) reenlistment bonuses entered the retention equation as integers describing the multiples that were offered.[1] For example, the Zone A multiple ranged from 0 to 6. The effect of a given bonus policy could be measured with reasonable precision, as long as the bonus program remained fixed. However, this approach could not be used to estimate the effect of bonus program changes, such as payment of bonuses in lump sums rather than installments, an increase in the bonus cap, or counting previously obligated service in the computation of the award. All of these policy options could be evaluated under the ACOL approach where the annuitized value of the bonus is computed.

The ACOL model is limited, however, in that it does not recognize that changes in reenlistment bonuses may also have lagged effects on retention. For example, the ACOL model predicts that the expected future man-years of service from one who reenlists in the presence of a level six bonus are the same as from one who reenlists while receiving no bonus. To the extent that the higher bonus induces a "reluctant" soldier to continue his military career, this will not be the case. By modeling the conditional distribution of unobserved "tastes" for military service, models in the post-ACOL generation adjust their predictions of future retention for the effects of past compensation policies.

III. Early Reenlistment Research

Some of the earliest work on enlisted retention behavior includes research that was done for the Gates Commission. The decision to establish a volunteer force rested, in part, on the budget cost of increasing retention and lowering the demand for accessions under a volunteer force. Hence, an estimate of the increase in reenlistments that could be anticipated under alternative pay policies was needed. Grubert and Weiher (1970) estimated reenlistment equations for first-term Navy enlisted personnel using a functional form that was linear in the natural logarithm. Wilburn (1970) estimated the effects of the draft and pay on the retention of first-term Air Force enlisted personnel under a logit specification, and Nelson (1970) analyzed first-term Army reenlistments using a log-linear specification.

This early work clearly established the empirical relationship between enlisted retention decisions and key variables such as military pay, potential civilian earnings, and draft pressure.[2] As an example of the results from these studies, the elasticity of reenlistment with respect to military pay was estimated to be in the range between 2.0 and 2.5. While it was an excellent beginning, much room was left for further research. Data limitations, computational cost, and the state of econometric methods undoubtedly precluded more ambitious efforts.

Specific methodological problems were as follows:

- The empirical specifications of the models, while plausible and generally related to the theory of occupational

choice, were not derived rigorously from an underlying utility maximization framework. An exception is a paper by Altman and Barro (1970) on the supply of officers, which presents a theoretical model of the decision to enter military service much like that found in the more recent retention literature.

- Only first-term reenlistment decisions were modeled, limiting the applications of the research in assessing compensation effects.
- Insufficient attention was paid to the institutional details of the military personnel system, such as the distinction between reenlistments and extensions.
- The functional forms chosen for estimation often were less than ideal. For example, some did not constrain the reenlistment rate to lie within the unit interval. Others placed constraints without theoretical justification.
- The horizon over which military and civilian pay were compared was arbitrarily chosen. Typically, authors evaluated relative pay over a three- to four-year period, the length of another term of service. Some, however, assumed that the military career would include the retirement vesting point and, therefore, included retirement benefits in the computation.
- The problems created by truncation and selectivity bias were not yet appreciated in the econometrics literature and, as a result, the early efforts did not test for these problems.
- The estimated coefficients were accepted as structural coefficients from a supply equation without addressing the possibility of simultaneity bias induced by the allocation of occupation-specific pay, such as bonuses.
- The models were estimated using grouped data resulting in a loss of information and, possibly, aggregation bias.

Much of the work has stood the test of time quite well, however. For example, based upon the analysis of first-term retention in the Army, it was predicted that the Army would achieve a career ratio (percentage of the enlisted force with

more than 4 years of service) of 46.4 percent. The actual career ratio at the time was approximately 29 percent. In FY 1985, the actual career ratio was about 46 percent!

Several other studies from this period deserve note. Enns (1975, 1977) estimated the effects of variable reenlistment bonuses and selective reenlistment bonuses for first-term personnel in all services. Although the work did not represent a significant advance over previous efforts, it did produce estimates of the effects of bonuses on reenlistment rates that were used by defense analysts through the early 1980's.

Rodney et al. (1980) estimated models of the first- and second-term reenlistment decisions in the Navy using data from the 1973–1979 period. Cross-sectional and time-series observations were pooled by skill in a variance components model that accounted for unobserved skill-specific and time-specific effects. The study is distinctive in that two wage variables were specified in the same equation—one for a horizon of four years and another for a longer horizon extending to the retirement vesting point—presumably letting the data themselves provide the implicit weights to the two career paths.

IV. Annualized Cost of Leaving (ACOL) Model

The first major departure from the early literature was the development of the ACOL model by Nelson and Warner. The major contributions of the model were that (1) it provided a rational basis for determining the horizon over which military and civilian pay are compared, and (2) it related the estimated retention equation more directly to individual utility-maximizing decisions.

The importance of comparing pay over the correct "horizon" is apparent when evaluating the effect of a change in the military retirement system on first- or second-term reenlistments.[3] The military retirement system offers a real annuity of 50 percent of basic pay for life to those who leave after completing 20 years of military service. Those who leave prior to completing 20 years receive nothing. The predicted effect of a change in the retirement system depends on whether the horizon for comparing expected military and civilian compensation at a particular reenlistment decision point extends to the 20-year

point. If it does not, the model would predict no effect on reenlistments at that decision point. Prior to ACOL, these horizons were determined in an *ad hoc* fashion, depending upon the problem at hand. In ACOL, the horizon is endogenously determined by the time paths of military and civilian pay.

The ACOL model can also be viewed as an attempt to derive the reenlistment equation directly from assumptions concerning individual utility maximization. Though the degree of success in this regard is a matter of some debate, the ACOL model and the literature it has generated ensure that consistency with utility maximization is a criterion by which all work in this area will be judged.

The ACOL model is developed as follows. For an individual at year of service (YOS) t, the expected returns to remaining s more years in the military are

$$(1) \qquad RS_s = \sum_{j=t}^{t+s} d^{j-t} M_j + d^{s+1} [R_{t+s} + W_{t+s}]$$

where

RS_s is expected present value of the income stream from s more years of military service;

M_j is expected military pay in year j, $j=t,...t+s$;

R_{t+s} is expected present value of the retirement income stream if the individual serves t+s years;

W_{t+s} is expected present value of the civilian wage stream if the individual serves t+s years; and

d is $1/(1+\rho)$ where ρ is the individual's rate of time preference.

The returns to leaving immediately are

$$(2) \qquad RL = R_t + W_t$$

where R_t and W_t are the present value of the retirement income and civilian wage streams, respectively, if the individual leaves at time t.

Now let δ be the individual's annual net preference for the nonpecuniary aspects of military versus civilian life. This can be thought of as the amount the individual would be willing to

pay each year to stay in the military if annual military and civilian compensation were the same. The individual will prefer a strategy of remaining s more years to leaving immediately only if

$$(3) \qquad RS_s - RL + \sum_{j=t}^{t+s} d^{j-t}\delta > 0, \text{ or}$$

$$COL_s > -\sum_{j=t}^{t+s} d^{j-t}\delta$$

where COL_s is the financial cost of leaving now rather than staying s more years. Note that $-\delta$ is the individual's net preference for *civilian* life. Dividing both sides of the equation by $\Sigma\, d^{j-t}$, the decision rule can be rewritten as stay if

$$(4) \qquad ACOL_s > -\delta$$

where ACOL is the annualized cost of leaving.

The ACOL criterion for choosing the horizon of future services that is relevant for retention decision making is easily derived. The individual will stay if there is at least one horizon s for which the annualized cost of leaving exceeds the value of the net nonpecuniary benefits of civilian life. That will be true only if

$$(5) \qquad \max_s ACOL_s > -\delta$$

If δ is assumed to be distributed $F(\mu,\sigma)$, the unknown parameters of the ACOL model can be estimated by maximum likelihood methods. Both logistic and normal distributions have been used in empirical work.

A logit specification of the model was first estimated by Warner (1979), using grouped cross-section Navy data from years of service (YOS) 4 through 16. This procedure resulted in reenlistment pay elasticities of between 2 and 3 at the first-term point. Chipman (1979) and Enns, Nelson, and Warner (1984) have also estimated the model in this manner, with similar results.

Since its formulation, versions of the ACOL model have been applied to several services and to a number of different problems. Warner (1982) estimated a sequential logit version of the model for both the first-term and second-term reenlistment decision in the Marine Corps, using grouped data over the FY 1977–78 period. A reenlistment was defined as a commitment of an additional three years or more and an extension was defined as a commitment of less than three years. Warner first estimated the probability of staying, then estimated the probability of reenlisting or extending conditional on staying. Hence, the decisions were structured as a sequential process.[4] He found that pay elasticities with respect to the stay decision were generally in the range of 1 to 2 at the first term, and in the range of 1 to 3 at the second term. The elasticities varied with occupational category. Zulli (1982) estimated a sequential logit model for enlisted personnel in the Navy making their third reenlistment decision. He found an all-Navy pay elasticity of less than 1.

Goldberg and Warner (1982) examined first- and second-term reenlistments in the Navy over the period FY 1974–80. A conditional logit model was used to estimate the probabilities of reenlisting and extending versus leaving the Navy, at each of the two decision points independently. Their conditional logit formulation improves upon the sequential decision model assumed in the Marine Corps analysis.[5] Using grouped data, Goldberg and Warner found pay elasticities for the stay decision of 1.1 to 2.7 at the first-term decision point and 0.9 to 3.8 at the second term. Somewhat surprisingly, given the differences in method, these elasticities were in the same range as those found by Warner (1979).

The Goldberg-Warner model also included a measure of expected sea duty and the civilian unemployment rate. The effects of these variables were in the hypothesized direction. Longer expected durations of sea duty were associated with lower retention rates, though the effect was estimated imprecisely. An increase in the civilian unemployment rate was estimated to raise both the first- and second-term retention rates. Finally, the first-term bonus received by those facing their second-term reenlistment decision was also included in the model; it entered with a negative sign. The interpretation

is that large first-term bonuses induce those with a lower average taste for service to reenlist. Hence, this group will reenlist at a lower rate than an otherwise similar group which did not enjoy a first-term reenlistment bonus. Inclusion of the (lagged) first-term bonus at the second reenlistment point is an *ad hoc* method of adjusting for the "taste" distribution, the importance of which is discussed in the next section.

V. Dynamic Reenlistment Models

Both Warner (1981) and Fernandez et al. (1985) have described the ACOL model as being internally inconsistent in its explanation of the pattern of retention rates over years of service. Consider the expected rate of retention at the first-term reenlistment point

$$(6)\quad r_1 = pr(ACOL_1 > -\delta) = pr(-ACOL_1 < \delta) = \int_{-ACOL_1}^{\infty} dF(\delta)$$

where the subscripts denote the term and the "maximum" on the ACOL variable is implied. All those with a "taste for service" variable, δ, less than $-ACOL_1$ will leave. Therefore, after the first-term decision, the taste distribution becomes truncated at $-ACOL_1$.

At the second reenlistment point for this cohort, if the value of ACOL is $ACOL_2 > ACOL_1$, the model implies that the second-term reenlistment rate will be unity. More generally, the model predicts that, for a given cohort, if

$$(7)\qquad ACOL_t > \min\{ACOL_{t-1}, ACOL_{t-2}, \ldots\}$$

then the reenlistment rate at that point will be 1. In fact, ACOL values do tend to rise with years of service, largely because of the retirement system, yet the reenlistment rates do not approach unity until about the 14th year of service. Hence, the model's prediction is inconsistent with the empirical evidence.

Moreover, the way the model has been estimated in the past has been inconsistent with its logical structure. If at the first-term reenlistment point the distribution of the taste component is normal, the distribution of tastes at the second-term decision will be truncated normal, with the truncation point equal to (the negative of) the first-term value of ACOL.

The actual second-term reenlistment or retention rate will depend not only upon the second-term value of the financial incentive to stay, but also upon the first-term retention rate (or ACOL value). Typically, the ACOL model has been estimated in a way that assumes the distribution of "tastes for service" at any given decision point is independent of the distribution of tastes at prior years.[6] It is as if the model's structure were simply: reenlist if $ACOL_t + \varepsilon_t > 0$, where ε_t is identically and independently distributed over time.

A second-term reenlistment or retention equation that does not take into account the retention or survival rate up to that point will be estimated imprecisely and perhaps with bias.[7] For example, a cohort that experienced a loss rate of 90 percent at the first-term point is likely to have a much different retention rate at the second-term decision point than a cohort which enjoyed a 10 percent loss rate at the first-term reenlistment point, other things being the same. Hence, while a model may predict well for some policy changes, its predictions will become increasingly erroneous as the censoring in the taste distribution deviates from its historical pattern.

This problem is simply a manifestation of the more general problem of "unobserved heterogeneity." Individuals differ by unobserved or unmeasured factors. If these factors affect their behavior in a systematic way, then the choices that individuals make will be systematically correlated with the unmeasured factors. In the military personnel system, individuals who remain in military service will tend, on average, to have unmeasured factors that increase the probability of staying, relative to the probability of staying conditional only upon the observable factors. Conversely, those who possess unmeasured factors that tend to reduce the probability of staying will tend to select themselves out of the military. Hence, the distribution of these unobserved factors affecting retention behavior will change in a systematic way, as a given entry cohort passes through successive reenlistment decision points. Since ACOL values tend to rise with years of service, failure to account for the censoring in this unobserved "taste" component will result in an ACOL coefficient that is biased upward in a longitudinal analysis. If, on the other hand, both the individual's financial incentive to stay and his "tastes" are

positively correlated over time, cross-sectional estimates of the effect of compensation on second-term (and beyond) retention will be biased downward.

ACOL-2 Model

The ACOL-2 model represents a recent effort to overcome the self-selection problem of the ACOL model. It captures many of the desirable economic properties of a more rigorous dynamic retention model (see next section), while retaining the simpler structure of the ACOL model.

The ACOL-2 model is derived from the original ACOL model in that it uses the same financial incentive variable—the Annualized Cost of Leaving (ACOL). The ACOL-2 model, however, differs importantly in its handling of unobserved heterogeneity, or tastes, that underlie the self-selection process, by explicit inclusion of a transitory random error affecting reenlistment behavior at each decision point.

The ACOL-2 model overcomes two major shortcomings of the original ACOL formulation. First, it provides an internally consistent explanation of why reenlistment rates are not unity beyond the first-term of service, an erroneous literal prediction of the simple ACOL model. Second, it corrects for the selectivity bias that may result from failing to account for unobserved heterogeneity in a multidecision model. That is, it recognizes that reenlistment rates will rise with years of military service because those who stay have a stronger taste for military service than otherwise similar persons who leave. Failure to account statistically for this unobserved heterogeneity may result in biased coefficients on measured variables, such as the financial returns to staying, if these variables are correlated with the changing taste distribution over time.

In the ACOL-2 model unobserved factors are divided into two components: the fixed taste component, δ_i, and a transitory random term, ε_{it}. This error term structure is referred to as a one-factor variance components model. With this revision, an individual's decision rule is to reenlist if

$$\text{ACOL}_{it} + \delta_i + \varepsilon_{it} > 0 \qquad (8)$$

In terms of its *theoretical* formulation, the ACOL model includes δ_i but excludes ε_{it}. In terms of its *empirical* specification, the ACOL model includes ε_{it} but excludes δ_i because the latter is unobservable in cross-sectional models. A major contribution of ACOL-2 is that its empirical specification includes both δ_i and ε_{it}, which is consistent with its theoretical underpinnings. The ACOL-2 model is more complicated to estimate than the original ACOL model; we describe the estimation procedure in the appendix.

The ACOL-2 model has been used in a variety of retention contexts. Black, Warner, and Arnold (1985) originally used the model to analyze annual quit rates of DoD civilian employees over the first 10 years of service. Black, Hogan, and Sylwester (1987) developed and estimated an ACOL-2 model of first-, second-, and third-term reenlistment decisions for Navy enlisted personnel. Finally, Smith and Sylwester (1988) used a modified version of the ACOL-2 approach in modeling the retirement decisions of DoD civilians.

A contribution of the original ACOL model is that it addressed the horizon issue and focused attention on the individual-specific, unmeasured factors affecting reenlistments, the taste component. Unfortunately, the statistical procedures used to estimate the model could not accommodate unobserved heterogeneity (tastes) implied by the theoretical formulation of the model. The ACOL-2 specification explicitly adjusts for the effects of unobserved heterogeneity in a statistically sound manner. Since the ACOL values are undoubtedly correlated with the changing distribution of the unobserved component over military years, this adjustment will remove this source of bias from the estimated ACOL coefficient.

Dynamic Retention Model

The Dynamic Retention Model (DRM), also called the Stochastic Cost of Leaving (SCOL) Model, developed by Gotz and McCall (1980), offers an alternative solution to the dynamic selection problem. Like the ACOL-2 model, retention is specified as a function of a cost of leaving (COL) variable, an individual-specific taste parameter, δ_i (assumed to remain fixed over time), and a transitory stochastic term, ε_{it}, that is random across individuals and time. The transitory error term

includes all unobservable factors excluded from the model that are unrelated to the unknown permanent taste variable.

The major difference between the DRM and ACOL-2 is the calculation of the financial cost of leaving variable. In ACOL-2, the financial variable is the annualized difference between military and civilian pay, where the horizon (or additional years of service) is the one that maximizes the annualized difference between military and civilian pay. It is the financial variable found in the ACOL model, recomputed for each reenlistment decision.[8]

In the DRM the expected return to staying is calculated as a weighted average of the returns to staying over all possible exit points. The "weights" are endogenously determined and represent the probability that the individual will leave at each of the respective years of service.[9] The computation of the expected returns to staying at least one more period in the Gotz-McCall formulation assumes that individuals know the distribution of the transitory component. Based upon this (known) distribution and (known) future military and civilian pay streams, individuals compute the probability of leaving at each possible year of continued service. This computation of the financial incentive to stay is consistent with rationally formed expectations of the returns to staying at least one more period. However, sophistication of the Gotz-McCall formulation is purchased at a price. The model is quite difficult to estimate, much less tractable for policy analysis, and less flexible in incorporating nonpay variables than is the ACOL-2 model.

The empirical significance of the differences between the Gotz-McCall and ACOL-2 models depends on the changes in compensation being analyzed. Fernandez et al. (1985) discuss some of the problems caused by neglecting pay beyond the optimal horizon, while Hogan (1985) discusses a case where neglect of periods less than the calculated optimal horizon may result in misleading inferences. For most general pay and bonus changes, and for many types of changes in the retirement system, they should generate similar predictions. However, for radical changes in the compensation system, such as a restructuring of the military retirement system, the Gotz-McCall model may generate better predictions, at least in theory.

However, since the Gotz-McCall and ACOL-2 models are caricatures of the more complicated real world, one cannot say *a priori* whether these differences would necessarily be borne out in practice.

Arguden (1986) analyzed the differences in predictions of the original ACOL model and the Gotz-McCall model for a number of alternative policy changes. He concluded that ". . . adding a taste proxy [to the ACOL] model (which is a function of the proportion of an entering cohort still in the military at a particular decision point) greatly improves the model's predictive ability (i.e., the predictions come closer to those of the Gotz-McCall model). Estimation of a variance-components model along with the inclusion of a taste proxy is likely to reduce the biases even further. Any additional variable that explains some of the variance of the random shocks, such as the unemployment rate, is also likely to reduce the biases."

VI. Other Modeling Issues

In addition to the issues already discussed, there are a number of other problems that typically arise in formulating and implementing reenlistment models. For some issues, the theoretical and empirical implications for reenlistment research have been thoroughly explored. In other cases, the issues have been identified but generally ignored in the literature.

Effects of Compensating Wage Differentials

Goldberg and Warner (1982), among others, have found that the supply of personnel to military occupations considered more onerous in nature also tends to be less wage elastic. However, the estimated effect of pay on retention in those occupations may be negatively biased. Bias will arise if the nonpecuniary aspects of the occupation affect retention adversely, but are unmeasured or measured with error, and special pays or bonuses are used to partially offset the adverse retention effects.

Hosek and Peterson (1985) estimated a trichotomous logit model for both the first- and second-term retention decision using grouped data from all the services over the period FY 1976–81. The choices analyzed were reenlist, extend, or leave.[10] A major contribution of the Hosek and Peterson paper

is the explicit treatment of potential simultaneity bias in estimating the effect of reenlistment bonuses on retention. Hosek and Peterson provide a solution for this problem by measuring the explanatory variables as deviations from their means, a fixed effects model. This is equivalent to allowing each occupation to have its own intercept term, thereby "measuring" differences across occupations in nonpecuniary factors.

Individual's Personal Discount Rate

The discount rate affects how the "cost of leaving" is measured in any model that considers future as well as current compensation. With the exception of a change in bonuses from installment to lump-sum payments, there has been little of the type of pay variation necessary to measure the discount rate of military personnel.[11] Hence, reliance has been placed upon survey results (e.g., Black, 1983, and Nord and Schmitz, 1985) and external estimates. Note that the discount rate makes the greatest difference precisely in those types of pay changes that have not been frequently observed, such as changes to the retirement system.

Post-Service Earnings Data

Structural reenlistment models, such as ACOL, require predictions of the expected post-service earnings streams of enlisted personnel making a reenlistment decision. However, we only observe post-service earnings for those who leave. If members who leave have better civilian earnings opportunities than those who stay and our specification of the earnings model does not capture the difference—both reasonable assumptions—the earnings model will provide biased predictions of post-service earnings. This, in turn, may bias the estimated pay effects. This is an example of sample selection bias.

Econometric methods have been developed to deal with this problem, but their application to post-service earnings models has been limited by the quality of the data available to estimate such models (see Daula, 1981, and Goldberg and Warner, 1983 and 1987). Daula and Baldwin (1986) argued that "...the thrust of reenlistment research should turn to assembling better data sets with particular attention to the civilian earnings data for veterans."

Risk Aversion

There is much evidence suggesting that individuals are risk averse. Applied to occupational choice theory, individuals will prefer an occupation with lower earnings dispersion to one with higher dispersion, other things being equal. Daula (1981) and Daula and Baldwin (1986) have noted that neither ACOL nor any other retention model has incorporated risk aversion.

Incorporation of risk aversion is not difficult in concept, but requires strong assumptions to implement empirically. For example, assume that individuals have a utility function that is a quadratic in income, Y, such as $U = aY - bY^2$. Then, if individuals act as if to maximize expected utility, E[U], the expected utility of a given occupation is $aE[Y] - bVar[Y]$, where "E" is the expectations operator and "Var" is the second moment. Hence, occupations should be compared not only by mean earnings, as is done in current retention models, but also by the difference in the second moment of the distribution. The problem in this specification would be to obtain a reasonably good estimate of the second moment of the earnings distribution. Finally, if the measures of dispersion are constant over time, the issue of risk aversion may be moot.

Optimal Decision Rules, Constraints, and Choices

Observed relationships between individuals and the environment are the result of the interaction of individual optimizing behavior, the constraints placed upon the individuals, and the choices or opportunities they face. When the constraints change, behavior will change. According to this view, behavioral changes cannot be predicted from econometric models that accept the original relationship between individual behavior and the existing constraint as a structural relationship. The estimated model may "fit well" over any particular historical episode, but the behavioral relationships captured in the model will not predict the effects of major policy changes well. Instead, the econometric model should be formulated in terms of the "deeply embedded" parameters of tastes and technology, if one wishes to predict the effects of large changes in the policy environment.[12]

Within the military retention literature, this criticism has been applied almost exclusively to the ACOL model though it

is clear that the point is general. The ACOL model has been the key model for estimating the effects of the type of major policy change that epitomizes this critique—a major structural change in the military retirement system.[13] There are at least two reasons why the ACOL model's estimates of such a change should be interpreted with caution. First, current retention behavior produced by current compensation policy is embedded in the structural coefficients. This is the point made in this section. Second, a radical change in the retirement system may cause portions of an underlying taste distribution to become relevant for the first time. Since our information concerning this portion of the distribution may be poor, the estimates are subject to greater uncertainty. Better modeling may be able to alleviate the first type of problem, although we are forced to bear the second type of uncertainty.[14]

Expectations

Considering the emphasis placed on future as well as current levels of military pay and compensation in the retention literature, the neglect of an explicit analysis of how individuals form expectations of future pay levels when considering a decision to remain or to leave military service is surprising. Nevertheless, virtually all researchers have assumed a version of static expectations—individuals are assumed to act as if the time path of military and civilian pay observable in the current cross-section at the time of their decision will persist indefinitely.

In fact, a case may be made that, over long periods of time, relative pay tends to remain roughly constant. Periods of abnormally large military pay increases tend to be followed by periods of relatively smaller increases, restoring an equilibrium. Indeed, there is an exigency to keep pay reasonably competitive in order to continue to attract and keep qualified people. Hence, rational individuals would not act as if a current pay raise that was abnormally high or low would permanently (or over their multiperiod horizon) raise or lower relative military pay. Instead, the "permanent" level of relative military pay would be determined by "real" factors such as the desired size and quality level of the Armed Forces relative to the rest of the labor market. Rational individuals would perceive deviations from longer run averages as "temporary."

Only if real factors changed, such as a decrease in the size of the Armed Forces due to a general relaxation of international tensions, would the rational individual perceive a permanent change. This does not mean that short-run deviations from the perceived permanent level of military pay will not affect retention behavior. Rather, it means that changes that are permanent will have a greater effect on retention behavior than similar changes that are temporary. Unfortunately, there are no models in the literature that have explicitly explored more rational mechanisms of expectations formation.

VII. Summary

We have reviewed the methodological development of retention models from the Gates Commission to the present. The models have become increasingly sophisticated in both their theoretical development and empirical implementation. This has improved their usefulness for policy analysis by expanding the range of issues that can be reliably evaluated. Yet, significant shortcomings and gaps remain in the literature. As described in the overview, many of these shortcomings will be addressed and some of the existing gaps narrowed in the papers that follow.

Appendix : Dynamic Retention Models

This appendix outlines the specification and estimation of the ACOL-2 and Stochastic Cost of Leaving models.

ACOL-2 Model

The ACOL-2 decision rule is: Reenlist if $ACOL_{it} + \delta_i + \varepsilon_{it} > 0$. Assume that $\varepsilon_{it} \sim N(0,\sigma_\varepsilon)$ and $\delta_i \sim N(\mu_\delta,\sigma_\delta)$. The probability that individual i reenlists at time t is

(A.1) $$p(t) = pr[-(ACOL_{it} + \delta_i) < \varepsilon_{it}]$$

$$= \int_{-ACOL_{it}-\delta_i}^{\infty} dF(\varepsilon)$$

where F is the cumulative normal distribution function for ε. Because of the symmetry of the normal distribution, this is equivalent to

(A.2) $$p(t) = \int_{-\infty}^{ACOL_{it}+\delta_i} dF(\varepsilon) = F[ACOL_{it} + \delta_i]$$

The probability that an entering individual survives at least to time T is

(A.3) $$S_{it} = \prod_{t=1}^{T} p(t) = \prod_{t=1}^{T} F[ACOL_{it} + \delta_i]$$

For an entire entry cohort, the survival rate through time T is

(A.4) $$S_t = \int_{-\infty}^{\infty} \prod_{t=1}^{T} F[ACOL_{it} + \delta_i]\, dG(\delta)$$

where G is the cumulative normal distribution function for δ.

Given the normality of δ, $g = (\delta - \mu_\delta)/\sigma_\delta$ is a standardized normal variable with density $\phi(g)$, and

$$\delta = \sigma_\delta g + \mu_\delta$$

Since ε_{it} is distributed normally, $\varepsilon_{it}/\sigma_\varepsilon$ is a standard normal variable. Finally, let Z be a vector of all other factors affecting reenlistment behavior, such as education and unemployment

rates, with β a vector of parameters to be estimated. Making these substitutions and suppressing individual subscripts, we can rewrite equation (A.4) as

$$\text{(A.5)}\quad S_t = \int_{-\infty}^{\infty} \prod_{t=1}^{T} \Phi\left\{[ACOL_t + (\sigma_\delta g + \mu_\delta) + \beta Z] / \sigma_\varepsilon\right\} \phi(g)dg$$

$$\text{(A.6)}\quad = \int_{-\infty}^{\infty} \prod_{t=1}^{T} \Phi\,[\alpha_1 + \alpha_2 ACOL_t + \alpha_3 g + \alpha_4 Z]\,\phi(g)dg$$

where $\alpha_1 = \mu_\delta/\sigma_\varepsilon$, $\alpha_2 = 1/\sigma_\varepsilon$, $\alpha_3 = \sigma_\delta/\sigma_\varepsilon$, and $\alpha_4 = \beta/\sigma_\varepsilon$. The parameters of this model can be estimated using a quadrature procedure described in Butler and Moffitt (1982).[15]

Define the correlation coefficient, ρ, as

$$\text{(A.7)}\quad \rho = \sigma_\delta^2 \,/\, (\sigma_\delta^2 + \sigma_\varepsilon^2)$$

Then, $\rho / (1-\rho) = \sigma_\delta / \sigma_\varepsilon$, which is the coefficient α_3. Hence, the coefficient α_3 in equation (A.6) measures the importance of unobserved permanent versus transitory factors in explaining reenlistment rates over time. When $\rho = 0$ (σ_δ is very small and σ_ε is very large), there is no permanent "taste" factor affecting retention rates over military service. One could then model multiple reenlistment decisions as if they were independent events. Hence, the empirical specification of the original ACOL model, which ignores tastes, would not create problems due to unobserved heterogeneity in a multiperiod case.

When $\rho = 1$ (σ_δ is very large and σ_ε approaches zero), unobserved heterogeneity or tastes dominate the effects of transitory disturbances. Reenlistment rates should rapidly approach unity after the first reenlistment point. Hence, controlling for tastes in a multiperiod framework becomes increasingly important as ρ approaches 1.

Dynamic Retention Model

The Dynamic Retention Model model can be interpreted as follows. For individual i making a retention decision at t,

$$\text{(A.8)}\quad SCOL_{it} = \sum_{s=1}^{t} P_{s,it}\,[COL_{s,it} + \sum_{k=1}^{s} d^{k-1}\,\delta + \sum_{k=2}^{s} d^{\,k-1}\,\varepsilon^{*}_{it+k}]$$

where $COL_{s,it}$ is the observable financial cost of leaving rather than staying through period s; $\sum_{k=1}^{s} d^{k-1}\delta$ is the present value of the "taste" factor; and $\sum_{k=2}^{s} d^{k-1}\varepsilon^*_{it+k}$ is the expected present value of the random disturbance, ε^*, conditional on staying to period s (s>1). $P_{s,it}$ is an endogenously determined probability that the individual will leave in period s, given that he stays in period t. Since $\sum P_{s,it} = 1$, SCOL, the individual's stochastic cost of leaving, can be interpreted as a weighted average of the cost of leaving at all possible future leaving points.

After calculating $SCOL_i$ for each individual, the retention criterion is to stay if $SCOL_i + \varepsilon_{it} > 0$, where ε is the transitory error factor. Thus the individual stays if $\varepsilon_{it} > -SCOL_i$. The DRM handles the self-selection problem in an internally consistent fashion. For given values of μ_δ, σ_δ, and σ_ε, and a specified military compensation system, the model predicts the whole career pattern of survival and retention rates. A simulation analysis by Warner (1981) demonstrated that the model can accurately predict the pattern of retention rates under the current compensation system and that it gives plausible predictions of the effects of various changes in the system.

It is assumed that the transitory errors are distributed according to the normal cumulative probability function $F(\varepsilon)$ with mean 0 and standard deviation σ_ε. Thus, the probability that the ith individual will remain in service from year 1 through year t is

$$\text{(A.9)} \qquad \prod_{j=1}^{t} \int_{-SCOL_{ij}}^{\infty} dF(\varepsilon_j)$$

We may now derive the survival rate of a whole cohort of individuals from year 1 through year t. Assume that $G(\delta_i)$ is distributed normal with mean μ_δ and standard deviation σ_δ. The survival rate to year t of the personnel in this initial cohort is

$$\text{(A.10)} \qquad S_t = \int_{-\infty}^{\infty} \{\prod_{j=1}^{t} \int_{-SCOL_{ij}}^{\infty} dF(\varepsilon_j)\}\ dG(\delta_i)$$

where the conditional retention rate at YOS t is $r_t = S_t/S_{t-1}$. While this formulation looks mathematically formidable, it simply weights the survival probabilities of different personnel in the initial cohort by the relative frequencies of different values of δ_i.

Notes

1. Reenlistment bonuses are specified as the product of monthly basic pay, the number of months that a soldier extends his military commitment, and a bonus multiple. The multiples are set separately for three years-of-service zones, corresponding to reenlistments at the end of the first (A), second (B), and third (C) terms.

2. This last variable can be interpreted as an early attempt to account for the underlying taste distribution of potential reenlistees, a theme that receives increasing attention in the later literature.

3. In fact, ACOL was developed to analyze exactly this problem.

4. A potential weakness of the sequential logit model is that it assumes that unobserved factors influencing the stay-leave decision are independent of the unobserved factors affecting the reenlist-extend decision.

5. The conditional logit model, however, is a poor choice in the analysis of extensions versus reenlistments because it constrains reenlistment bonuses to reduce extensions by the same percentage that it reduces losses. As reenlistments and extensions are close substitutes, the conditional logit model's "independence of irrelevant alternatives" assumption may be particularly inappropriate to an analysis of reenlistments versus extensions.

6. Warner and Simon (1979) estimated a second-term retention model which included the first-term ACOL value in an *ad hoc* attempt to adjust for the changing taste distribution.

7. If the unobserved factors are correlated with the explanatory variables, the estimated coefficients may be biased.

8. Note that the horizon will differ across decision points and across individuals if the time paths of military and civilian earnings differ.

9. The appendix to this section describes the DRM in more detail.

10. The study is reminiscent of Goldberg and Warner (1982), but the model is clearly outside of the ACOL framework for (at least) two reasons. First, the pay variable was specified as an index of current military pay relative to civilian pay, and the reenlistment bonus entered as a separate variable. There is no financial variable analogous to a "cost of leaving." Second, the specification is unrelated to the random utility model of choice behavior implicit in the conditional logit model used by Warner and Goldberg.

11. See, for example, Cylke et al. (1982).

12. Lucas (1976) was among the first to make this argument in the context of econometric models used for macroeconomic policy evaluation. Sargent (1981) applied the observation to a more general class of econometric models, emphasizing the point made here that "...people's behavior will change when their constraints change."

13. The Fifth QRMC, the Office of the Secretary of Defense, the Department of the Navy, and the Congressional Budget Office, for example, have used versions of the ACOL model to estimate the effects of proposed changes to the military retirement system on enlisted retention.

14. A frequently heard objection to simulations of proposed policy changes is that they ". . . require extrapolation beyond the range of experience over which the parameters were estimated." Those making this point usually mean that the model has not identified the structural parameters of the system.

15. If only two decisions are being modeled, one can also estimate the parameters by noting that $\delta_i + \varepsilon_{i1}$ and $\delta_i + \varepsilon_{i2}$ are distributed bivariate normal. For censored observations—individuals leaving after the first term—the contribution to the likelihood function will be a simple probit; for those making two decisions, a bivariate probit with correlation parameter ρ.

3

Army Reenlistment Models

D. Alton Smith
Stephen D. Sylwester
Christine M. Villa

I. Introduction

Every year over 100,000 enlisted personnel in the U.S. Army face a reenlistment decision. Understanding what factors influence those decisions, and by how much, is necessary information for successfully managing the size and composition of the enlisted force. With 15 years of experience under the market-driven manning system known as the All-Volunteer Force (AVF), the correlates of Army reenlistment rates are by now well known.

For two reasons, however, there is far less agreement about the size of the effects that key policy variables, such as military pay, have on the reenlistment decisions of Army personnel. First, the last major studies of Army reenlistment behavior were based on enlisted personnel making decisions almost 10 years ago. Significant changes in the Army since that time raise the possibility that the results from those studies are no longer valid. Second, the sensitivity of estimated parameters to the assumptions employed in modeling the reenlistment decision, an issue raised in previous studies, has not been fully investigated. A full understanding of the empirical conse-

quences of alternative methodological approaches is important in deciding how to use the results from reenlistment models.

In addition, the existing studies of Army reenlistment behavior are limited in scope, dealing only with decisions at the end of the first term or only with certain Army occupations. A broader perspective is required to meet the forecasting and policy evaluation needs of personnel analysts.

The objective of this analysis is to fill in some of the gaps in our quantitative understanding of Army reenlistment behavior by estimating econometric models of the first- and second-term reenlistment decisions in three Career Management Fields (CMFs)—Infantry, Mechanical Maintenance, and Administration. We focus on the first- and second-term decision points because, given the pyramid-like structure of the enlisted force, this is where knowledge of reenlistment behavior can have the most influence in helping the Army meet its enlisted personnel requirements. A broad coverage of occupations is also desirable as the effects of changes in military pay and other policies on reenlistment will be different for soldiers with varying opportunities in the civilian sector. To meet this objective while allowing a careful investigation of methodological issues, we have selected one CMF from each of three broad occupation groups in the Army—combat, technical combat service support, and nontechnical combat service support.

In Section II we derive a theoretical model of the reenlistment decision, describe the sources of the data used in the estimation, and discuss issues in the empirical specification of the model. Our reenlistment model starts with the Annualized Cost of Leaving, or ACOL, model for decisions at the end of the first term. The ACOL model incorporates many of the special features of the reenlistment decision, including consideration of both pecuniary and nonpecuniary differences between a military and civilian career, the importance of evaluating the lifecycle effects of reenlistment, and the problem of selecting a military career horizon over which compensation should be evaluated. Because these theoretical advantages are combined with relatively straightforward estimation, the ACOL model is the most commonly used approach in reenlistment modeling.[1]

If, as seems reasonable, there is an individual-specific component in the unobserved factors affecting reenlistment, decisions at the end of the second term will be linked to events at the first-term decision point through the censoring of these "tastes" for military service. Thus, there are advantages to jointly estimating first- and second-term ACOL reenlistment decision models, an approach that has been called the ACOL-2 model. Although our estimation procedures are different from the original ACOL-2 formulation, this is essentially the approach we will take.

The estimation of ACOL-2 models requires longitudinal data on individual soldiers. We use a new data set, the Enlisted Panel Research Data Base (EPRDB), which was constructed in conjunction with this study (See Section II and Appendix B). Based primarily on personnel records maintained by the Defense Manpower Data Center (DMDC), it tracks a random sample of AVF soldiers who enlisted from FY 1974 through FY 1984 with snapshots of information at accession, annually during active duty, and at separation.

In Section II we also discuss three general specification issues that arise in implementing the ACOL model. The most complicated is how to obtain the estimates of future military and civilian compensation required to calculate the ACOL variable. As military compensation is the sum of component pays which are, in turn, functions of a soldier's professional and personal characteristics, we first predict those characteristics and then directly calculate military compensation from the appropriate pay tables. The key unknown characteristic is the soldier's pay grade at future years of service; we estimate promotion time models to provide this information.

For civilian compensation, we estimate post-service earnings models using a DMDC data set that contains IRS earnings for veterans who left the Army's enlisted ranks between 1972 and 1980. The estimated parameters of the post-service earnings models are potentially biased because earnings are only observed for veterans, not for all soldiers making a reenlistment decision. Although a formal sample selection bias test is not feasible given the characteristics of the earnings data set, we do estimate an ACOL model with a reduced form specifica-

tion of post-service earnings to assess the potential bias from this source.

In addition to the earnings projections, the ACOL calculations require assumptions about the soldier's discount rate and about the implicit model used for forming expectations about the general level of future military pay compared with civilian compensation. Our "baseline" model uses a 10 percent discount rate and assumes static expectations, but we alter both assumptions in estimating the model to test the sensitivity of the pay effects.

The second issue involves the specification of variables related to the nonpecuniary returns to a military or civilian career, the "taste" variables. As many of these variables, such as race and the presence or absence of dependents, are also correlated with relative compensation, estimated pay effects are sensitive to these specification choices. To the contemporaneous taste variables typically included in reenlistment models, we add variables measured at the accession point, such as the length of the initial term and the education benefits for which a soldier is eligible. As choices made by the individual when enlisting indicate initial tastes for military service, differences across time in these choices may help to "explain" the large cohort effects often found in reenlistment models.

Reenlistment rates are a function of Army demand as well as the supply decisions made by soldiers. To correctly measure the effect of relative pay and other variables on reenlistment decisions, it is important to isolate the demand factors in the estimation process. One way demand impinges on soldiers' reenlistment choices is through reenlistment eligibility. The question here is whether to control for eligibility directly by estimating reenlistment models only for eligibles or indirectly by including eligibility-related characteristics in the reenlistment model. For both theoretical and empirical reasons, we take the latter approach but also test the sensitivity of our estimates to this assumption.

There is also institutional evidence that, over the period of our analysis, the Army became more active in managing reenlistment rates among soldiers who were nominally eligible to reenlist. For example, the interpretation and enforcement of reenlistment goals, set by Headquarters and distributed

through the chain of command to Noncommissioned Officers charged with the responsibility for reenlistment activities, changed substantially. These management effects are not easy to quantify, but we do include variables that are potentially correlated with the effects in our "baseline" specification. We also reestimate the reenlistment models for relevant subsamples of the enlisted population to test the sensitivity of our initial estimates.[2]

Section III presents the estimation results. First, we outline the characteristics of the soldiers in the three CMFs, with special emphasis on how the annualized cost of leaving varies across groups. Next, we describe the parameter estimates for the Infantry CMF, for which we have the best reference point in the existing literature. Then, we compare and contrast the reenlistment model estimates for the Mechanical Maintenance and Administration CMFs. Finally, we examine the effect of changing some of our specification assumptions on the estimated first-term pay elasticity for infantry soldiers. Our findings are summarized at the end of this section.

II. Reenlistment Decision Model

In this section, we specify a joint model of the first- and second-term reenlistment decisions for Army enlisted personnel in the Infantry, Mechanical Maintenance, and Administration Career Management Fields. The section is divided into three parts describing the theoretical model, data sources, and empirical specification issues.

Starting from a general model of occupational choice, we first derive the ACOL reenlistment model, noting the assumptions that take us from the general formulation to the specific. Because it captures the key features of the reenlistment decision in a way that allows for relatively straightforward estimation of the unknown parameters, the ACOL model has been the most commonly used approach in the reenlistment literature. Recently, the ACOL framework was extended to provide a theoretically consistent model of reenlistment decisions over multiple terms of service. This extension, called the ACOL-2 model, is the methodology we use in this analysis.

Then, we describe our primary data source, the Army Research Institute's Enlisted Panel Research Data Base

(EBRDB). This data set, which was constructed in conjunction with this analysis, provides a rich source of longitudinal information for a sample of Army personnel who enlisted during the period of the AVF.

Estimation of the ACOL-2 model involves a number of empirical specification issues, such as how to predict future military compensation for soldiers making a reenlistment decision. Alternative specifications, each with a reasonable economic or statistical justification, may lead to different parameter estimates. As a goal of this analysis is to test the sensitivity of the estimated models, we devote considerable effort to describing these specification issues and the summary of the results later in this section.

The ACOL-2 Reenlistment Model

The decision to reenlist or enter the civilian sector can be viewed as a special case of the general problem of occupational choice. In choosing an occupation, an individual evaluates the pecuniary and nonpecuniary returns, over the planning horizon, for each occupation in his or her choice set and selects the one providing the greatest utility. This concept of the occupational choice process can be expressed mathematically in the following decision rule. An individual chooses occupation j (or, more generally, a career path of occupations) to

$$\text{(1)} \qquad \max U = \sum_{1}^{T} U\,(Y_{jt}, N_{jt})d^{t}$$

where periods 1 to T are the planning horizon, Y_{jt} represents the expected real compensation from occupation j in period t, and N_{jt} denotes the expected nonpecuniary returns.[3] Future utility values are discounted by $d = (1+r)^{-1}$, where r is the individual's real discount rate.

This model is too abstract to be estimated; functional forms relating parameters to observable characteristics must be specified first. The ACOL model, developed in Warner (1979), is the specification of this general model that has been used most extensively in studying reenlistment behavior. We will describe the model in the context of a soldier making a reenlistment decision after his or her first term of service. The

choices are to leave the Army now or stay through some future term of service and then leave.

To specify the lifecycle utility associated with these choices, the ACOL model assumes that utility in each period is a linear function of compensation and nonpecuniary factors,

$$U_{ijt} = \alpha_i + \beta_i Y_{ijt} + \lambda_i N_{ij} \tag{2}$$

where α_i, β_i, and λ_i are taste parameters for individual i. The linearity assumption, as noted by Daula (1981), is inconsistent with a diminishing marginal utility of income, a common assumption in specifying utility functions. However, the linear form allows the reenlistment decision rule to be specified in dollar terms, rather than utility, which is convenient in interpreting and using the model. Note that we also assume that the nonpecuniary factors associated with an occupation for each individual do not vary over time. While perhaps not realistic, this assumption is consistent with our limited ability to measure these nonpecuniary factors in practice.

If the soldier leaves the Army after the first term, we can combine equations (1) and (2) to express lifecycle utility as

$$UC_i = \alpha_i \sum_1^T d^t + \beta_i \sum_1^T WC_{it}\, d^t + \lambda_i NC_i \sum_1^T d^t \tag{3}$$

where period 1 is the first year after leaving, the WC's represent the real value of post-service compensation in the civilian labor market, and the nonpecuniary factors associated with civilian employment are given by NC.

Following the literature, we assume in equation (3) that a soldier cannot reenter the military after he or she leaves. This is not literally true, but very few soldiers follow this type of career path for two reasons. First, the Army restricts the number of prior-service accessions it will accept. And second, the Army penalizes interrupted service by generally allowing reentry only at a lower pay grade than the soldier had attained at separation. Making this assumption, of course, significantly reduces the number of career paths that must be considered in the reenlistment model.

If the soldier stays in the Army until year s, utility can be expressed as

$$(4) \qquad UM_i = \alpha_i \sum_{1}^{T} d^t + \beta_i \left[\sum_{1}^{s} WM_{it} d^t + \sum_{s+1}^{T} (WC_{ist} + R_{ist}) d^t \right]$$

$$+ \lambda_i \left[NM_i \sum_{1}^{s} d^t + NC_i \sum_{s+1}^{T} d^t \right]$$

The financial returns to this choice include military earnings, WM, for years 1 through s, as well as civilian compensation and military retirement benefits, R, for the remainder of the planning horizon. The nonpecuniary returns to this choice include NM during the individual's military career, followed by NC.

Note that we have specified retirement benefits and civilian pay as a function of the date of separation from military service, s. Military retirement benefits are zero until the vesting point at 20 years of service and increase with years of service beyond that point. Studies of post-service earnings, such as Goldberg and Warner (1987), find that the labor-market returns to military experience are generally smaller than the returns to civilian experience. Thus, annual post-service income is a function of the soldier's years of military service at separation.

Given these two choices, an individual will reenlist if UM–UC > 0, or

$$(5) \quad \beta_i \left[\sum_{1}^{s} (WM_{it} - WC_{it})\, d^t + \sum_{s+1}^{T} (WC_{ist} - WC_{it} + R_{ist})\, d^t \right]$$

$$> \lambda_i (NC_i - NM_i) \sum_{1}^{s} d^t$$

Dividing equation (5) by β_i and $\Sigma\, d^t$, we obtain the decision rule expressed in dollar terms. That is, the individual will reenlist if

$$(6) \qquad \frac{\sum_{1}^{s}(WM_{it} - WC_{it})\, d^t + \sum_{s+1}^{T}(WC_{ist} - WC_{it} + R_{ist})\, d^t}{\sum_{1}^{s} d^t}$$

$$> (\lambda_i / \beta_i)\,(NC_i - NM_i)$$

The left side of equation (6) is the cost of leaving the Army, annualized over the additional years of military service. The cost of leaving has several components. Between years 1 and s, there is the discounted present value of the difference between military and civilian compensation, WM–WC. The decision to stay or leave also has effects after the military career is over. To the extent that military experience is valued less highly in the civilian labor market than civilian experience, the cost of leaving is increased by the loss in earnings potential, WC_s–WC. Offsetting this, however, are any military retirement benefits.

As λ_i and β_i represent the marginal utility associated with the pecuniary and nonpecuniary aspects of an occupation, the ratio of these two terms is the dollar value of a "unit" of the nonpecuniary factor. Therefore, the right side of equation (6) is the dollar value of the annual difference between the nonpecuniary returns to civilian and military careers. The soldier will reenlist, then, if the ACOL is greater than the annual benefits from the nonpecuniary factors of a civilian versus a military career.

To this point, we have developed the model implicitly assuming a particular horizon of future military service, s. In fact, there are multiple horizons—one more term of service, two more terms, etc., all of which imply reenlisting at the current decision point. A rational individual will reenlist if there is at least one horizon where the ACOL exceeds the relative nonpecuniary benefits of a civilian career. Such a horizon exists if the maximum ACOL across all possible horizons is greater than the nonpecuniary benefits, or

$$(7) \qquad \max_{s} ACOL_i > (\lambda_i / \beta_i)\,(NC_i - NM_i)$$

This is the ACOL decision rule.[4]

The advantage of the ACOL model is that, unlike the models that preceded it, there is a rational way to decide, for each individual, the appropriate horizon to use in constructing the financial variable for a reenlistment model. Moreover, the methodology is straightforward to implement. With predictions for WM, WC, and R, we can calculate ACOLs for various horizons and choose the maximum before actually estimating any parameters.

There are two limitations to the ACOL framework as a model of first-term reenlistment decisions (we discuss problems in the application of the ACOL model to second-term and later decisions below). First, a discount rate must be assumed to calculate the maximum ACOL. As different discount rates will lead to different ACOL values and, possibly, different pay effects, it would be preferable to estimate the discount rate as a parameter of the reenlistment model.

Second, as noted by Fernandez et al. (1985), among others, the assumption of a single horizon over which the cost of leaving is calculated is not realistic. For example, an implication of this assumption is that changes in military pay beyond the horizon have no effect on the current retention decision. A more general approach is to calculate expected returns to continued military service by weighting the compensation streams for all possible horizons by retention probabilities. This is a feature of the Dynamic Retention Model, developed in Gotz and McCall (1980), and the Stochastic Cost of Leaving Model, outlined in Warner (1981). However, the additional reality in these models comes at significant computational cost because the financial variable is now a function of endogenous retention probabilities.[5]

The monetary value of the nonpecuniary returns to military and civilian careers in the ACOL decision rule, which varies with the individual, cannot be observed. To provide an estimable ACOL model, we assume that these factors are a function of individual characteristics and an error term, yielding a new decision rule,

(8) $$\max_{s} ACOL_i + X_i\delta > \gamma_i$$

where X is a vector of individual characteristics and γ is a random error term. If we assume that γ is distributed $N(0,\sigma_\gamma)$, then the probability that individual i reenlists at decision point n is given by

$$\text{(9)} \qquad pr\,(ACOL_i + X_i\delta > \gamma_i) = \Phi\,[(ACOL_i + X_i\delta)/\sigma_\gamma]$$

where Φ is the cumulative normal distribution function.[6] The unknown parameters of this equation can be estimated using a probit model.

When the ACOL model in equation (8) is applied to second-term and later reenlistment decisions, a problem in the specification of the nonpecuniary factors is revealed. Consider a cohort of soldiers with the same ACOL value at the first-term reenlistment point, $ACOL_1$. Only those with unobserved "tastes" for a civilian career, or a γ, less than $ACOL_1$ reenlist at the end of the first term.[7] This means that the distribution of the γ's at the second-term reenlistment decision will be upper truncated, with the truncation point at $ACOL_1$. Typically, the ACOL value at the second decision point, $ACOL_2$, will be greater than $ACOL_1$ because of the effect of the retirement system on the cost of leaving. When this is the case, the second-term reenlistment rate predicted from the ACOL model is 1 (because $\lambda_i<ACOL_1<ACOL_2$ for all soldiers at the second-term decision point), which is much higher than the rates actually observed.

The problem is that the original ACOL model assumes that a soldier's evaluation of the relative nonpecuniary returns to a military career remains constant across reenlistment decisions. A more realistic assumption is that there is a transitory component in this evaluation, which results from new information collected as a soldier moves through his or her career, as well as the constant component associated with individual tastes.

The ACOL-2 model, first applied to the retention behavior of DoD civilians in Black et al. (1985), modifies the ACOL decision rule to include both components, so that a soldier reenlists if

$$\text{(10)} \qquad \max_s ACOL_{in} + X_{in}\delta > \gamma_i + \varepsilon_{in}$$

where ε is an error term measuring transitory effects on reenlistment decision n. It is assumed to be uncorrelated across reenlistment decisions.[8] Because of the ε's, the combined error distribution at the second-term reenlistment point will no longer be truncated and, therefore, predicted reenlistment rates do not necessarily go to 1 when ACOLs rise across terms. Below we show how the composition of the total error in terms of constant and transitory components affects the second-term reenlistment rate.

To estimate the ACOL-2 model for first- and second-term reenlistment decisions, we define $\eta_{in} = \gamma_i + \varepsilon_{in}$ and assume that η_1 and η_2 are distributed bivariate normal, $N(0,0,\sigma_\eta,\sigma_\eta;\rho)$, where ρ is the correlation between the η's. The four possible reenlistment patterns in our data and their associated probability expressions are

1. Leave at first term:

   $$pr\ (ACOL_{i1} + X_{i1}\delta < \eta_{i1}) = \Phi\ [-(ACOL_{i1} + X_{i1}\delta) / \sigma_\eta]$$

2. Reenlist at first term, but second-term decision not observed:[9]

   $$pr\ (ACOL_{i1} + X_{i1}\delta > \eta_{i1}) = \Phi\ [(ACOL_{i1} + X_{i1}\delta) / \sigma_\eta]$$

3. Reenlist at first and second terms:

$$pr\ [(ACOL_{i1} + X_{i1}\delta > \eta_{i1}) \text{ and } (ACOL_{i2} + X_{i2}\delta > \eta_{i2})] = \Phi_B\ [(ACOL_{i1} + X_{i1}\delta) / \sigma_\eta, (ACOL_{i2} + X_{i2}\delta) / \sigma_\eta, \rho] \tag{11}$$

4. Reenlist at first term, leave at second:

   $$pr\ [(ACOL_{i1} + X_{i1}\delta > \eta_{i1}) \text{ and } (ACOL_{i2} + X_{i2}\delta < \eta_{i2})] = \Phi_B\ [(ACOL_{i1} + X_{i1}\delta) / \sigma_\eta, -(ACOL_{i2} + X_{i2}\delta) / \sigma_\eta, -\rho]$$

where Φ_B is the bivariate cumulative normal distribution function. The parameters of the model can be estimated by maximum likelihood methods.[10]

Using equation (11), we can write the probability of reenlisting at the second term as the probability of reenlisting at both terms divided by the probability of reenlisting at the first term, or

$$\frac{\Phi_B\ [(ACOL_{i1} + X_{i1}\delta) / \sigma_\eta, (ACOL_{i2} + X_{i2}\delta) / \sigma_\eta, \rho]}{\Phi\ [(ACOL_{i1} + X_{i1}\delta) / \sigma_\eta]} \tag{12}$$

Two implications about the probability of second-term reenlistment can be drawn from this expression. First, note that the probability is a positive function of ρ. Given the definition of the η's, ρ equals $\sigma^2_\gamma/\sigma^2_\eta$, or the proportion of the total error variance due to individual-specific factors. This means that second-term reenlistment rates are a direct function of the importance of individual-specific tastes in the reenlistment decision. When individual taste differences are large relative to the transitory component, we expect higher reenlistment rates, other things equal, because those soldiers who value the nonpecuniary attributes of civilian employment are more likely to leave at the end of the first term.

The other implication of equation (12) is that second-term reenlistment rates will, in general, depend on the values of ACOL and the X's at the *first-term* decision point.[11] This means that probit models of second-term reenlistment behavior, which only include explanatory variables measured at that point, may be potentially biased because of the omitted variables. Predictions from these models will also be affected. For example, second-term models estimated with cohorts who experienced relatively high military pay at the first term may not predict well for cohorts who first reenlisted when pay was low.

One alternative is to include first-term variables directly in the second-term model, as Warner and Simon (1979) do to examine the second-term reenlistment effects of first-term bonus payments.[12] The other approach, which we take here, is to directly estimate the parameters of the structural model.

Enlisted Panel Research Data Base

Estimating the ACOL-2 model requires longitudinal data that tracks individual soldiers through first- and second-term reenlistment decisions. The Enlisted Panel Research Data Base, or EPRDB, which was created to provide an improved data source for Army manpower research, contains longitudinal information on a 1-in-4 sample of all Army enlisted personnel who entered military service from FY 1974, the start of the AVF period, through FY 1984. Each sample member is tracked at annual intervals until separation or the end of the data in 1987.[13]

The EPRDB contains information from three sources. Defense Manpower Data Center (DMDC) cohort, master, and loss records provide the core data. Information from the accession point, such as entry test scores and the education benefits program for which a soldier is eligible, is drawn from the cohort files. The fiscal year-end master files provide the annual updates, with data on career characteristics, such as grade and military occupation specialty (MOS), and personal characteristics, such as number of dependents and educational attainment. The loss records indicate the date and conditions—reenlistment eligibility, type of discharge—of a soldier's separation from the Army. For later years, the DMDC data is augmented by additional variables selected from the records maintained by the Army's Personnel Command (PERSCOM) and by Skill Qualification Test (SQT) scores obtained from the Training and Doctrine Command (TRADOC).

A significant problem in studying reenlistment decisions over a long period is maintaining data consistency. A primary example of the problem is the changing definitions of MOSs and how they are grouped in Career Management Fields (CMFs). To define CMFs for this study, we examined MOS lists and the number of personnel in each MOS at two-year intervals over the analysis period. Starting with the MOSs currently in the Infantry, Mechanical Maintenance, and Administration CMFs, we worked backward in time, adding older MOSs that correspond to jobs currently in the CMF. For example, Administrative Specialists (MOS 71L), the largest MOS in the Administration CMF, were previously designated as Clerk-Typists (71B). Thus, we have tried to identify all soldiers throughout the analysis period who worked in occupations similar to those currently in the CMF.[14]

In the next sections, we describe the empirical implementation of the ACOL-2 reenlistment model. We discuss specification issues related to the definition of a reenlistment, outline our approach to calculating ACOL values, and specify the other variables we include in the reenlistment model.

Definition of Reenlistment

The reenlistment process does not fit neatly into the dichotomous choice framework posited in ACOL models, and

the choices made in making it fit may affect the parameter estimates in the reenlistment model. There are four major issues—early "decisions," reenlistment eligibility, extensions, and reenlistment to retrain in a different MOS.

Early Decisions. There are two ways a soldier's first term can end more than several months before his Expiration of Term of Service, or ETS, date—attrition or early reenlistment. Table 3.1 displays attrition rates and early reenlistment rates for first-term soldiers in the Infantry, Mechanical Maintenance, and Administration CMFs. These rates are calculated from the EPRDB and, therefore, include soldiers who enlisted from FY 1974 through FY 1984. The attrition rate is defined as the proportion of an enlistment cohort that leaves the Army more than six months before their ETS date.[15] The early reenlistment rate is the proportion of first-term *reenlistments* in an enlistment cohort that occurred more than six months before ETS.

Table 3.1
Attrition and Early Reenlistment Rates[a]

Career Management Field	Attrition	Early Reenlistment
Infantry	.350	.086
Mechanical Maintenance	.322	.096
Administration	.308	.076

[a]For first-term soldiers. See text for definition of rates.

In estimating the reenlistment models, we remove from the sample any first-term soldiers who leave more than six months before their ETS.[16] In theory, attrition may censor the tastes (λ's) observed at the first-term reenlistment point in the same way that first-term decisions affect the tastes observed at the second-term ETS. Thus, the parameters of reenlistment models estimated conditional on survival to first-term ETS may suffer from the same type of omitted variable bias described above for second-term reenlistment models estimated only with soldiers who survive to the second-term ETS. Warner and Solon (1990) explore this issue by jointly estimating models of attrition and first-term reenlistment for soldiers in the infantry. When a rich set of regressors is included in

both models, they find no correlation between the errors of the attrition and reenlistment equations and, therefore, no bias in the estimated parameters of a conditional reenlistment model.

Early reenlistments are treated differently in our specification of the reenlistment model. At the first term, soldiers generally may reenlist up to six months before their ETS. However, if they are scheduled for an overseas assignment that would extend beyond their ETS, they may reenlist even earlier. These early reenlistments are included in the analysis sample, but we calculate their ACOLs at their initial ETS date, not when they made their reenlistment decision. As ACOLs rise rapidly during the initial years of service, evaluating relative pay at the decision point for early reenlistments while using the ETS point for soldiers who separate can impart a substantial downward bias to the estimated pay effects. For this reason, we "move" soldiers who reenlist early forward to their ETS point (including any predicted promotions) before calculating their ACOL.

Reenlistment Eligibility. Before a soldier can reenlist or extend, a soldier must be certified as eligible to reenlist. The general qualifications for reenlistment include the following:

- "Trainability," as measured by ASVAB and SQT scores;
- Educational attainment, which varies by occupation;
- Medical and physical fitness, including weight standards;
- Absence of serious disciplinary problems; and
- Minimum grade requirements by year of service.[17]

Waivers of eligibility requirements may be granted; whether a waiver is allowed and the level of command required to approve the waiver varies with the requirement. Table 3.2 shows eligibility rates at the first and second decision points using two definitions of eligibility, the Army code and the Interservice Separation Code (ISC).

Table 3.2
***Reenlistment Eligibility Rates*[a]**

Career Management Field	1st Term Army	1st Term ISC	2nd Term Army	2nd Term ISC
Infantry	.795	.853	.803	.831
Mechanical Maintenance	.783	.828	.782	.805
Administration	.852	.865	.844	.863

[a]Proportion of soldiers who are eligible to reenlist according to Army code (= 0,1) and ISC code (= 0,1,100) for a normal expiration of term of service. Calculated from the EPRDB.

Eligibility has been treated in different ways in the reenlistment literature. Some authors maintain that, as ineligible soldiers may not reenlist, they should be excluded from the sample for an analysis of voluntary reenlistment supply behavior. Daula (1981), however, argues that many of the actions leading to ineligibility are, in fact, a manifestation of the decision not to continue an Army career. For example, soldiers who turn down a required overseas tour have a reenlistment "bar" placed in their file; but if they accept the tour, the bar is removed. Excluding these individuals from a reenlistment model may introduce bias in the same way as including those who are ineligible for seemingly exogenous reasons, such as a medical problem.

The available data on reenlistment eligibility confounds the problem. Many of the reasons for ineligibility in the data, such as "unfitness," are so general that they are difficult to classify as exogenous or endogenous. In addition, eligibility screening may not be applied to all separations. Unless a commander decides to bar a soldier with disciplinary or other performance problems, eligibility is only determined if a soldier applies for reenlistment. Finally, because eligibility is only an issue if reenlistment is desired, the data may not be maintained as carefully as other information such as pay grade.

Given the problems in defining a truly exogenous measure of reenlistment eligibility, we estimate our baseline model without conditioning on eligibility.[18] Thus, our model is the

reduced form of a two-equation model of eligibility and reenlistment "intentions."[19] To obtain a consistent estimate of the parameters in this model, it is necessary to include the individual characteristics that would appear in a reenlistment eligibility equation, such as AFQT and education, but might not usually be considered for a reenlistment model. This guides the specification of the non-ACOL variables in our model, which is described later in this section. To check the sensitivity of our estimates to this treatment of eligibility, we also estimate the model conditioning on the strictest definition of reenlistment eligibility, the Army code.[20]

Extensions. Soldiers who are eligible to reenlist may generally extend their current term of service at the ETS point. Soldiers may also be required to extend if the time remaining in their current term does not allow completion of other requirements, such as a minimum overseas tour length. Table 3.3 displays the extension rate—the proportion of soldiers reaching ETS who extend—and the average extension length in months for soldiers in the three CMFs.[21] Extensions differ from reenlistments in two ways. First, extensions generally obligate a soldier for a shorter period of future service than a reenlistment, which is typically for three to four years. Second, soldiers who reenlist are eligible to receive reenlistment bonuses while soldiers who extend are not (unless their extensions are longer than three years).

Table 3.3
Extension Rate and Average Length[a]

Career Management Field	Extension Rate	Average Months
Infantry	.205	8.0
Mechanical Maintenance	.187	9.0
Administration	.251	12.0

[a]For first-term soldiers.

Extensions have been treated in different ways in the literature. Some studies effectively lump extensions and reenlistments together by modeling continuation or retention rates, the probability that a soldier at ETS is still on active duty a year later. The problem with this specification is that different

obligations of future service with different financial incentives are grouped together. Recognizing this, Goldberg and Warner (1983) and Lakhani and Gilroy (1986) estimate models with separate equations for reenlistments and extensions. Although conceptually the best approach, it would be impractical to model the extension-reenlistment-separate choice jointly at both the first and second ETS points. Instead, we simply "follow" soldiers who extend, by pushing their ETS date forward, until they reenlist or separate.

Retraining. Although the rules have changed over time, soldiers are generally allowed to switch their MOS when they reenlist. Table 3.4 shows the proportion of reenlistments that include a change in CMF in our data. The rates are highest for the Administration and Infantry CMFs and at the first-term reenlistment point.

Table 3.4
Proportion of Reenlistments With a CMF Change[a]

Career Management Field	First Term	Second Term
Infantry	.116	.089
Mechanical Maintenance	.055	.023
Administration	.128	.037

[a]Calculated from the EPRDB.

As Daula (1981) notes, pooling soldiers who change occupations with those who reenlist in the same occupation is conceptually inappropriate because job-changers generally forfeit a reenlistment bonus in exchange for new skills and/or a different military "lifestyle." Given the relatively low frequency of CMF changing, we will not expand the choice set to include separate options for reenlistment with and without a job change. However, we do censor those individuals who leave a CMF at the first-term reenlistment point and will test alternative assumptions about assigning bonuses to switchers (see the discussion of predicting military compensation below).

Computing the ACOL Variable

The ACOL variable, defined in equation (6), requires predictions of the expected military and civilian compensation

streams for soldiers at a reenlistment decision point. We discuss our prediction methodology for each element in turn.

Military Compensation Predictions. While on active duty, enlisted personnel receive four general types of compensation—basic pay, allowances for housing and subsistence, the reenlistment bonus, and a wide variety of special pays and other benefits. Military compensation also includes post-service payments, such as retirement pay and education benefits.[22] At any point in time, each of these components is an exact function of soldier characteristics, such as years of service and pay grade. Therefore, if we know or can predict the appropriate characteristics for an individual, we can directly calculate his or her military compensation stream.[23] In what follows, we briefly describe each component of pay and outline how we determine values of that component for individual soldiers. More details on data sources and estimation results can be found in Appendix C.

Basic pay is the largest component of military compensation. In any one year, it is a function of only two factors, years of service and pay grade, but the pay tables are adjusted annually. To calculate basic pay in any future year of service, therefore, we need to predict the soldier's pay grade in that year and assume something about his or her expectations of future adjustments to the pay table.

In this analysis, pay grade predictions through E-6 are generated from promotion time models estimated from the Enlisted Panel Research Data Base for soldiers in each CMF. We use a log-normal hazard model to adjust for the censoring that occurs in promotion times as soldiers leave the Army and find that promotion times are, on average, longer for all soldiers at ETS than for soldiers who reenlist. As faster promotions indicate superior performance, it seems reasonable that soldiers who continue their military careers have shorter than average promotion times.[24]

We assume that promotion times are a function of both personal and professional characteristics and find that

- Promotion times are shorter for soldiers with more years of education and higher AFQT scores.

- Controlling for other factors, there is generally no difference between the promotion times of minority and nonminority soldiers.
- Female soldiers are generally promoted at the same rate as males, holding other factors constant.
- Soldiers who were promoted faster to previous grades have *slower* promotion times to the next grade. This is the result of minimum time-in-service requirements for promotion.
- Promotion speed varies over fiscal years because of changes in personnel requirements by grade relative to cohort sizes.

For promotions to E-7 through E-9, we use CMF-average promotion times calculated from FY 1986 data. Although a less attractive approach, there is limited longitudinal data on promotions of AVF soldiers to these grades.

We use two different models of the soldier's expectations about future adjustments in the basic pay table. Following most of the literature, our baseline specification incorporates static expectations. That is, we assume that the soldier expects the *general* level of relative military pay observed at the decision point to persist.[25] We also test a version of rational expectations in which the expected level of relative military pay is an autoregressive function of past levels. In this model particularly high or low relative pay levels at the reenlistment decision point are expected to return to a long-run average level.

The allowances received by enlisted personnel include the Basic Allowance for Quarters (BAQ), the Variable Housing Allowance (VHA), and the Basic Allowance for Subsistence (BAS), an allowance for meals. If the government provides housing or meals through a mess, these allowances are not paid. However, because we cannot assess the value of in-kind benefits, we include allowances in the compensation for all soldiers. All three allowances vary with grade, so the promotion time models are also used in assigning allowance amounts.[26]

In addition, housing allowances are larger for soldiers with dependents than for those without. We could assign these allowances based on the soldier's dependents status at the time

of the reenlistment decision, but this would understate expected military compensation for first-term soldiers without dependents because most will have dependents within four years. For example, at the first-term reenlistment point, 30 percent of the soldiers in the Infantry CMF have at least one dependent, but, by the end of the second term, the percentage has risen to 73 percent. To capture the effect of dependents on future pay, we use a lifetable to estimate the probability that the average soldier in a particular CMF, with no dependents at t years of service, would have dependents by t+1, t+2, and so on and weight the allowances accordingly. We assume that soldiers with dependents at the reenlistment point expect to continue to receive allowances based on this status.[27]

The reenlistment bonus for which a soldier is eligible is the product of the bonus multiplier in his occupation at his years of service, the number of additional years he adds to his service commitment by reenlisting, and his monthly basic pay. Thus, a soldier with a multiplier of one who reenlists for three more years receives a bonus equal to about 8 percent of his basic pay over the three years. Table 3.5 displays the average bonus multiplier for soldiers at first and second reenlistment decision points in the three CMFs. Multipliers are adjusted over time to meet personnel and budget requirements.

Table 3.5
Average Bonus Multipliers[a]

Career Management Field	First Term	Second Term
Infantry	1.154	.661
Mechanical Maintenance	.587	.272
Administration	.002	.001

[a]Calculated from our analysis files. See Appendix C.

Three issues arise in computing the reenlistment bonus amount. First, we assign the bonus for which a soldier would be eligible if he reenlisted at the current decision point, but we do not include any bonuses for future reenlistments. The alternatives would be to assume perfect foresight on the soldier's part, which is unreasonable given the time series variation in bonuses, and use actual bonus multipliers, or use an average

multiplier, which would shift everybody's military compensation up by a similar amount. Second, the method of paying reenlistment bonuses, as a lump sum or in installments, has varied over time, which has implications for the discounted present value of the bonus. We use the payment method in place at the time of the reenlistment decision.

Finally, as we have noted, soldiers who change their MOS at reenlistment are generally not eligible for a bonus, and we do not give them one in the baseline specification of our reenlistment model. However, to the extent that soldiers switch their MOS to increase their post-service earnings, the forgone bonus represents the minimum value of their new training. If it were less, they would not change occupations. As the value of this new training is not included in our projections of post-service earnings, it is appropriate to include the bonus as a proxy. We will test the sensitivity of our estimates to this alternative specification.

Military members also receive a variety of special pays and benefits that we do *not* include in our predictions of military compensation. Special pays, such as jump pay for paratroopers, are compensation for especially hazardous or arduous duties. As these pays are generally small relative to the total compensation package and are only offered when the individual is serving in a particular capacity, their exclusion does not have a substantial effect on our compensation predictions. Many of the other benefits received by soldiers, such as medical and dental care, life insurance, and vacation time, are also provided by civilian employers. As these benefits are difficult to value, we do not include them in either military or civilian compensation estimates. Where there is a substantial difference between the benefits provided in military and civilian occupations, such as the subsidized food prices in the commissary, we try to capture the effect by including soldier characteristics related to the value of the benefit, such as the number of dependents.

Post-service military compensation includes military retirement pay and education benefits. Participation in the military retirement system is vested with 20 years of service. Annual benefits are a function of basic pay at retirement and

the number of years served beyond 20, and are fully indexed to inflation. We calculate retirement benefits using our predictions of basic pay at 20 years of service and the benefits algorithm in effect when the soldier enlisted. Post-service education benefits differ from other forms of military compensation we have discussed in that they can only be used for education expenses. For this reason, we enter them separately in the reenlistment model rather than including them in the ACOL calculation (see the next section).

Post-Service Earnings. Future military compensation can be predicted more accurately than potential post-service earnings. Part of the explanation for this lies in the greater degree of structure found in the military compensation system as compared with the civilian sector. For example, years of work experience typically explains much more of the variation in military earnings than it does in civilian earnings because the military pay table is, by design, an explicit function of tenure. The ability to predict post-service earnings, however, has also been limited by the available data. There is no recent, individual-level data on the earnings of veterans that is comparable to the data we use to predict military earnings.

Our post-service earnings predictions are generated from models estimated with DMDC's Post-Service Earnings History File, or PSEHF, which contains earnings data on veterans who left the Army between 1972 and 1980.[28] We use the earnings information in the file that was collected from the Internal Revenue Service for the years 1979 through 1983. The advantages of the PSEHF for this analysis are the availability of post-service earnings for up to 12 years after separation, the relative timeliness of the data—other longitudinal files on veterans' earnings date from the early 1970's, and the good selection of potential explanatory variables.

There are, however, two major shortcomings to the PSEHF. First, there is no labor-supply information on the file. Military earnings are measured on a full-time basis. To correctly characterize the financial consequences of the choice between a military and civilian occupation, we should also measure post-service earnings net of any voluntary reductions in labor supply.[29] Our models of post-service earnings include variables to

measure changes in labor supply, but this is second best to actually observing full-time earnings.

Second, given the structure of the data in the PSEHF, our post-service earnings models must be estimated with grouped data. This severely limits our ability to test and correct for the selection bias that may occur in using the earnings experience of veterans to predict the potential post-service earnings of all soldiers at a reenlistment point.

We estimate separate earnings models for each CMF using the broad occupation groups available in the PSEHF. The dependent variable for these models is the natural logarithm of the mean of real, annual earnings for individuals in each group who had nonzero earnings. Using a specification derived from human capital theory and considerations specific to the military context, we find that

- Post-service earnings are, on average, highest for veterans who served as mechanics or craftsmen, followed closely by veterans from combat arms and administration-supply occupations.
- Post-service earnings increase with both military and civilian work experience but at a declining rate. The returns to the first year of civilian experience are around 8 percent; the returns to the first year of military experience vary from 3 percent to 5 percent. As veterans have, at a minimum, changed jobs (many change occupations, as well), a smaller return to military experience seems reasonable. Moreover, the difference between the returns to civilian and military experience is greatest for the combat occupations, where skills acquired in the military are less transferable to civilian employment.
- Earnings increase with a veteran's education at separation (approximately 4 percent per year) and are generally greater for those with higher AFQT scores. The earnings effects of a 30-point difference in AFQT (35 to 65) range from 0 percent to 7 percent across different occupations.
- Military performance, as measured by the veteran's grade at separation compared to the average grade

of separatees at the same year of service, is positively related to post-service earnings. A soldier who is half a grade ahead of his or her cohort at the first-term reenlistment point, which places him or her in approximately the top 15 percent in terms of promotion speed, has earnings between 7 percent and 8 percent higher, depending on the occupation. One explanation for this finding is that civilian employers value in their employees the same characteristics that the Army uses for promotion.[30]

- Earnings are lower than would be otherwise expected in the first year after separation, probably because of transitional unemployment or part-time work due to school enrollment.
- Earnings are also lower than expected for soldiers who separate between 13 and 19 years of service. As the vesting rules of the military retirement system provide a strong financial incentive for soldiers with more than 10 years of service to remain until 20, individuals who leave during these years are often "special" cases, such as disability retirements or separations for behavioral problems.
- Controlling for other variables, we find no difference between the post-service earnings of black veterans and others. However, we do estimate that female soldiers have substantially lower post-service earnings than males, between 40 percent and 60 percent depending on the CMF. This unusually large result is apparently not a function of labor supply reductions due to home production, as the difference is similar for females with and without dependents.
- Post-service earnings vary with the level of unemployment; a 1-point increase in the national unemployment rate is associated with a 1 percent to 2 percent drop in average earnings.

Post-service earnings predictions are generated from the models using a soldier's characteristics at the reenlistment decision point, the level of military experience corresponding to the horizon being evaluated, and increasing values of civilian

experience. We set the labor supply variables in the predictions to approximate full-time earnings. For example, we fix the national unemployment rate at the average for the sample and set the variable measuring the special year of service effects for YOS 13–19 equal to zero. We also ignore the female coefficient in the predictions. By comparison with the results on male-female earnings differentials in the labor economics literature, our estimates are too large, given that we control for occupation, on-the-job performance through the pay grade variable, aptitude in the AFQT score, and education. As the post-service earnings models are estimated in 1980 dollars, we adjust the earnings predictions for differences in the level of real earnings between the reenlistment decision year and 1980.

Constructing the ACOL Variable. Using these procedures for predicting military and civilian compensation, we generate compensation streams from the decision year through age 65 and calculate ACOL values for military careers involving three more years—the shortest reenlistment term—through 20 years of service. The maximum of these ACOLs is included in the model.[31] We use a real discount rate of 10 percent in calculating the ACOL, which is within the relatively wide band of discount rates defined by existing studies (see Hogan, 1982). To test the sensitivity of the estimates to the discount rate assumption, we also calculate ACOLs with 3 percent and 17 percent discount rates.

Other Variables

We include additional variables in the reenlistment model to control for three other factors affecting the reenlistment decision—differences across soldiers in their evaluation of the relative nonpecuniary benefits/costs of a military career, differences in the probability of meeting the eligibility standards for reenlistment, and differences in the state of the civilian labor market.

Race. Previous Army reenlistment studies, such as Daula and Baldwin (1986) and Lakhani and Gilroy (1986), have found that minority soldiers have significantly higher reenlistment rates, holding constant any racial differences in the relative pay variable. One possible explanation is that the Army is simply less discriminatory than society as a whole. Whatever

the reasons, we include dichotomous variables indicating if a soldier is black, Hispanic, or a member of some other minority group to measure racial differences in reenlistment rates.[32]

Dependents. The Army subsidizes the additional financial costs of family life beyond the difference in housing allowances that is already included in our estimate of military compensation. For example, the discount at the commissary is generally higher for the basic foodstuffs consumed extensively by families than for prepared foods used by singles. Another example is the subsidized daycare available on most Army installations. Given these financial considerations and intangible factors, such as a supportive environment for raising children, it is not surprising that Army reenlistment studies find that soldiers with dependents are more likely to reenlist, holding constant relative pay. We include the number of dependents that each soldier has at the reenlistment decision point to capture these effects.

Unemployment at Accession. Studies of enlistment supply behavior, such as Daula and Smith (1985), find that enlistment rates for "high-quality" youths, high school graduates with an AFQT greater than 50, rise with the unemployment rate. If the average taste for military service in the high-quality youth *population* is constant over time, one would expect that the average taste among high-quality *enlistees* is lower when unemployment is high because a larger fraction of the population is enlisting. Censoring of tastes at the enlistment point is a potential cause of large cohort effects, which are troublesome when the model is used for prediction. We include the unemployment in the state from which the soldier entered the Army and expect a negative sign.[33]

Post-Service Education Benefits. During the AVF period, individuals who enlisted in the Army have been eligible for post-service education benefits through programs such as the GI Bill, the Veterans Education Assistance Program (VEAP), and the Army College Fund (ACF). While education benefits programs have been shown to increase enlistments (see Fernandez, 1982, and Daula and Smith, 1985), the evidence is mixed on whether, as a payment received primarily after separation, they also reduce reenlistments.[34] For

example, Schmitz (1988) finds no reduction, while Hogan et al. (1990) do. To measure the effects of education benefits on reenlistment, we assign to each soldier the discounted present value of government-provided benefits in the program for which he or she is eligible.[35]

Length of Initial Term. Soldiers may enlist for two, three, or four years, although the choice of occupations and other enlistment options varies with the length of the initial term. For example, two-year enlistments have generally been available only for occupations in the combat arms. A reasonable supposition, which is supported in previous reenlistment studies, is that individuals who choose longer initial terms have a greater taste for military service, other things equal. We include the length of the initial term to control for these differences in tastes.[36]

MOS Dummy Variables. Different occupations in the Army can have very different lifestyles, which, in turn, affect reenlistment rates. For example, clerks in the Administration CMF generally work in an office setting and are only infrequently separated by work from their families. On the other hand, soldiers in the infantry spend a significant proportion of their work life in the field, away from their families. Much of this variation occurs across Career Management Fields and, for this reason, we will estimate separate reenlistment models by CMF. However, there may also be significant differences between MOSs within a CMF, so we group similar occupations together and define dummy variables for the groups.[37]

Other things equal, soldiers in an MOS with less attractive nonpecuniary attributes must be given higher bonuses to maintain reenlistment rates (see the difference between infantry and administration bonus multipliers in Table 3.5, for example). If we do not control for lifestyle differences in a model with pooled MOSs, these compensating differentials may bias the estimated pay effects downward. The MOS dummy variables provide some measure of control for these differences; we also estimate models with separate pay effects by MOS group.

Education, AFQT, and Relative Grade. Years of education, AFQT, and a soldier's grade relative to the average for his or her accession cohort serve two purposes in a reduced

form eligibility-reenlistment model. First, they are positively correlated with eligibility, either directly through the relationship to specific eligibility requirements or indirectly as indicators of military performance. Second, they may also be correlated with differences in tastes for military service. Given both effects, we cannot sign the relationship between these variables and reenlistment from *a priori* considerations alone. However, Daula and Baldwin (1986) find that, among soldiers in the Infantry CMF, reenlistment probabilities were higher for soldiers with faster-than-average promotions, holding constant relative pay. And, in their study of Navy reenlistment behavior, Black et al. (1987) find a negative relationship between AFQT and reenlistment rates.

Education is measured by years of completed schooling at the reenlistment decision point.[38] The AFQT score is taken from the soldier's accession record. Relative grade is his or her grade at the decision point minus the average grade for other members of the CMF who accessed in the same fiscal year.

Aggregate Eligibility Rate and Post-FY82. Previous Army reenlistment studies assume that, after controlling for reenlistment eligibility, observed reenlistments and separations are the result of soldiers freely evaluating their options. While this laissez-faire system was the rule for the early AVF years, recently the Army has become more active in managing the reenlistment process. Much of this activity has involved changes in the interpretation of reenlistment goals.

The process of setting and enforcing reenlistment goals can be loosely characterized as follows. Reenlistment goals, expressed as the number of reenlistments for first-term, mid-career, and career soldiers, are determined by Army Headquarters based on projected personnel requirements. They are distributed to the Major Commands (MACOMs), whose commanders determine how the goals are assigned to subcommands. The pressure that MACOM commanders place on their subordinates to meet these goals depends on two factors—the pressure they receive from Headquarters and the relationship between the goal and the usual reenlistment experience for units under their command.[39] At the local level, the reenlistment process is managed by reenlistment NCOs,

who receive badges and other recognition for meeting their reenlistment goals.

In FY 1985, first-term reenlistment goals were expanded to include a quality component. At reenlistment, "quality points" were calculated for each soldier based on civilian education, pay grade, SQT and GT (a weighted average of ASVAB subtests like the AFQT) scores, any reenlistment eligibility waivers in place, and the reenlistment option chosen. Quality-point goals, expressed as a minimum level for the average number of points among soldiers reenlisting, are distributed from Headquarters in the same fashion as the quantity reenlistment goals.

How changes in Headquarter's interpretation of reenlistment goals affect reenlistments can be illustrated by what happened in FY 1983. Faced with reenlistment rates higher than needed to meet personnel requirements, reenlistment goals were changed from a floor (that is, actual reenlistments were supposed to meet or exceed the goal) to a ceiling (reenlistments were to be no greater than the goal). Reenlistment rates dropped dramatically between 1982 and 1983—the first-term rate *among eligibles* fell from 58 percent to 41 percent—even though relative military-civilian pay was stable and unemployment rates were rising.[40]

To capture these reenlistment management effects, we include two additional variables in the model. Post-FY82 is a dummy variable equal to 1 if a reenlistment decision is made in FY 1983 or later. This variable roughly measures the period of active reenlistment management.

We also include the CMF eligibility rate in the decision year. If reenlistment NCOs play a role in encouraging or discouraging reenlistment, we would expect such activity to be a function of two factors—the soldier's performance and the pressure the NCO feels to meet reenlistment goals. We already include performance-related characteristics, such as AFQT and relative grade. The eligibility rate is a crude measure of the second factor. With stable personnel requirements, a higher eligibility rate, from either looser standards or a higher quality cohort, means that the Army can be more selective in whom it reenlists. Thus, we expect a negative correlation between the eligibility rate and reenlistment probabilities.[41]

Unemployment Rate. Unemployment reduces expected civilian earnings with no effect on military earnings. As our financial variable is based on full-time civilian earnings, we include unemployment rates separately to measure this effect. For first-term reenlistments, we use the national civilian unemployment rate for all 20- to 24-year-olds in the decision year. The unemployment rate for second-term decisions is for 25- to 30-year-olds.[42]

Summary

Starting from a general occupational choice framework, we have described an ACOL-2 model of first- and second-term reenlistment decisions. The model has the following features:

- Both the pecuniary and nonpecuniary aspects of the choice between a military and civilian occupation are considered.
- Because of the lifecycle context in which the model was developed, the relative compensation variable in the model, the annualized cost of leaving, reflects both current differences in military and civilian compensation as well as the post-service compensation effects of a military career.
- In principle, the decision to reenlist or not for an additional term involves the evaluation of the returns to military careers of different lengths. The ACOL framework provides a methodology, consistent with utility maximization, for collapsing this multiple-choice problem into a more practical dichotomous choice.
- A model of second-term reenlistment decisions should recognize that factors at the first-term decision point affect second-term reenlistment rates through the censoring of tastes for military service. The ACOL-2 provides a framework for estimating those effects.

We also described our approach for empirically implementing the reenlistment model. In this discussion, we identified many of the specification issues that, within the same theoretical framework, could lead to different estimates of key policy parameters. In the next section, after presenting the results

for our baseline model, we will explore the sensitivity of our estimates to two broad categories of specification issues. The first includes some of the assumptions required to calculate the ACOL variable, such as the specification of military and civilian compensation models and the choice of a discount rate. The second category involves the specification of "demand" effects on reenlistment rates. In this category, we include the treatment of reenlistment eligibility and the modeling of the Army's reenlistment management policies.

III. Estimation Results

This section describes the results of estimating the reenlistment models for the Infantry, Mechanical Maintenance, and Administration Career Management Fields. We present descriptive statistics for the samples used in the analysis, including a detailed examination of the ACOL variable. Next, we describe the parameter estimates for the Infantry CMF; the results for the other CMFs are contrasted and compared with those for the infantry. We then vary some of the assumptions used to calculate the ACOL variable and explore the effect on the estimated first-term pay elasticity of soldiers in the infantry. Lastly, we examine whether alternative approaches to controlling for demand factors affect the results obtained in the baseline model. The findings are summarized at the end of this section.

Analysis Samples

To construct the sample for each CMF, we start with all the individuals in the Enlisted Panel Research Data Base who accessed into the CMF between FY 1974 and FY 1984. Then we screen out soldiers who

- Accessed with prior military service;
- Enlisted for an initial term of service longer than four years;
- Separated more than six months before their first term ETS date;
- Were ineligible to reenlist because of death, entry into officer programs, or serious behavioral infractions; or

- Possessed incomplete or erroneous data.

Sample sizes and means for the resulting analysis samples are shown in Table 3.6.

First-term reenlistment rates vary from 32 percent for the mechanics to 44 percent for members of the Administration CMF.[43] The rates rise sharply by the second-term decision because of an increase in relative pay and because of the censoring of tastes for military service that occurs at the first decision point.[44]

Minority soldiers make up a significant proportion of all three CMFs, ranging from 29 percent in mechanical maintenance to 57 percent for administration at the first-term decision point. Note that the proportions rise significantly by the second-term decision, an indication of the higher reenlistment rates of minority soldiers.

The introduction of female soldiers is one of the significant changes that occurred to the Army's enlisted force over the period of our study. Female soldiers are barred from serving in combat arms occupations like the infantry and have been limited in the jobs they could choose in CMFs such as mechanical maintenance. Therefore, they are overrepresented, relative to their overall proportion in the enlisted force, in certain combat service support occupations, like the Administration CMF.

At the end of the first term, there is an average of one dependent for every two soldiers in these CMFs. By the second-term decision point, the number of dependents has tripled. This increase is due both to age and, as we will confirm later, the higher reenlistment rates for soldiers with dependents.

The typical soldier during the analysis period had a high school diploma (or GED) and AFQT scores at, or just below, the average for the U.S. youth population.[45] The Administration CMF has both the highest average years of education and highest average AFQT score, while the next most educated and highest scoring CMF is the infantry. These means obscure the fact that average AFQT scores and, to a lesser extent, average years of education have varied significantly over the AVF period. The average AFQT score for infantry soldiers at the first-term decision point was 55 in FY 1978. It declined to 35 in FY 1983 and rose to 51 by FY 1987. The experience in the other CMFs was similar.[46]

Table 3.6
Variable Means[a]

	First-Term Reenlistment			Second-Term Reenlistment		
	INF	MECH	ADMIN	INF	MECH	ADMIN
Reenlistment Rate	0.333	0.322	0.442	0.623	0.565	0.662
Black	0.242	0.199	0.467	0.361	0.306	0.597
Hispanic	0.065	0.048	0.049	0.071	0.051	0.047
Other Minority	0.049	0.041	0.051	0.053	0.047	0.055
Female	—	0.035	0.405	—	0.028	0.406
Initial Term (yrs)	3.349	3.404	3.202	3.463	3.473	3.277
AFQT (÷ 10)	4.472	4.117	5.016	3.996	3.797	4.586
Education Benefit[b]	4.513	4.203	4.722	5.209	5.289	5.456
Accession Unemployment (%)	7.491	7.468	7.494	6.724	6.723	6.814
Dependents	0.495	0.559	0.508	1.605	1.546	1.138
MOS1[c]	0.172	0.072	0.485	0.205	0.048	0.512
MOS2	0.084	0.118	0.300	0.116	0.074	0.336
MOS3	0.020	0.057	0.083	0.043	0.051	0.079
MOS4	—	0.371	0.022	—	0.483	0.029
MOS5	—	0.234	0.011	—	0.282	0.006
Education Years	11.740	11.710	12.340	11.850	11.880	12.380
Post FY 1982	0.515	0.503	0.498	0.841	0.802	0.715
National Unemployment (%)	11.650	11.680	11.570	7.562	7.499	7.701
Eligibility Rate (%)	79.580	78.220	85.170	80.260	78.150	84.440
Relative Pay Grade	–0.005	–0.011	–0.011	0.006	–0.011	–0.013
Sample Size	17,145	13,332	11,418	1,735	1,884	2,235

[a]First-term sample includes accessions from FY 1974 through FY 1984 who are still in the Army six months before their ETS date. See the text for other sample restrictions. The second-term sample is a function of first-term separations and data censoring.

[b]Discounted present value of government contributions in thousands of 1980 dollars.

Table 3.6 (continued)

[c]The MOS variables are

	Infantry	Mechanics	Adminstration
MOS1=	Indirect Fire (11C)	Weapons Repair (45B–45Z)	Administration Specialist (71L)
MOS2=	Heavy Anti-Armor Weapon (11H)	Utilities, Power Repair (52A–52F)	Personnel Specialist (75B–75F)
MOS3=	Fighting Vehicle (11M)	Construction Equipment Repair (62B)	Finance/ Accounting (73)
MOS4=		Wheeled Vehicle Mechanic (63B,63S,63W)	Legal/Court (71D,71E)
MOS5=		Tracked Vehicle Mechanic (63D,63E,63G,63H, 63J,63N,63R,63T, 63Y)	Physical Activity (03C)
Omitted Group=	Infantryman (11B)	Machine Repairer/ Machinist (41C,41J,44B, 44E)	Executive/ Chaplain Assistant (71C,71M)

The discounted present value (using a 20 percent discount rate) of post-service education benefits averaged about $4,500 (in 1980 dollars) over the analysis period. There was also significant time series variation in these benefits. Soldiers making first-term reenlistment decisions through FY 1980 have the highest average education benefits because many of them enlisted under the most generous program, the Vietnam-era GI Bill. It was followed by the least generous benefits package, VEAP, which was augmented with "kickers" in the period between FY 1979 and FY 1982, finally emerging as the Army College Fund in FY 1983. Although the benefits under the ACF were nearly as generous as the GI Bill, participation was limited to high-quality soldiers who enlisted in certain occupations. Thus, the average benefit remained below the level of the GI Bill, which was available to all veterans.

Most soldiers in these CMFs enlist initially for three- and four-year terms of service. Two-year enlistments were limited to certain occupations in certain years; overall, less than 5 percent of the sample enlisted for this initial term.

As we noted in the last section, there are two sources of information on reenlistment eligibility—the Army reenlistment code, which we use in this analysis, and the Interservice Separation Code, which is based on the Army code and other separation information such as the type of discharge. In our sample, the Army definition is generally stricter (see Table 3.2). The variation in the Army eligibility rate over time also parallels more closely the quality of the reenlistment cohorts we described above. For example, Army eligibility rates are lowest in FY 1983, when the average AFQT of soldiers making a first-term reenlistment decision also reached its nadir, but there is little change in the ISC rate. For this reason, we think the Army rate provides a better test of the reenlistment management hypothesis posed in the previous chapter.

Two other results in Table 3.6 deserve comment. First, the variation across the accession and national unemployment rates is a function of the unemployment rate used, not the point at which unemployment is measured. Unemployment at accession is for labor force participants 16 and older; the national unemployment rates are for younger (20- to 24-year-old) participants only. Second, the average relative pay grade should be zero given the definition of the variable. It differs somewhat from zero because the sample used to calculate the average pay grade for accession cohorts differs slightly from the analysis sample.

Because of its central importance to the analysis, we will examine in more detail the remaining variable in the reenlistment model, the ACOL, using the results in Table 3.7. At the first-term decision, ACOLs are highest for the Infantry CMF and lowest for administration. As post- service earnings are roughly similar across the CMFs for individuals leaving at the end of the first term (see Table D-1), this ordering is produced primarily by differences in military compensation, particularly reenlistment bonuses. Over the analysis period, first-term soldiers in the infantry were offered the highest bonus multipliers; soldiers in administration, the lowest (Table 3.4).

Table 3.7
Average ACOLs by Group

Group	ACOL	Group	ACOL
CMF and Term:		Decision in:[a]	
First Term		FY 1978	3.374
Infantry	4.429	FY 1979	3.224
Mechanics	3.687	FY 1980	3.085
Administration	2.194	FY 1981	4.690
Second Term		FY 1982	5.683
Infantry	7.378	FY 1983	5.251
Mechanics	5.871	FY 1984	5.222
Administration	5.879	FY 1985	4.880
Education:[a]		FY 1986	4.640
< High school	4.755	FY 1987	4.227
High school diploma	4.431	Race:[a]	
> High school	3.058	White	4.356
AFQT:[a]		Black	4.643
< 50	4.706	Hispanic	4.353
≥ 50	3.931	Other Minority	4.427
Relative Grade:[a]		Sex:[b]	
< Mean grade	4.981	Male	2.188
≥ Mean grade	3.962	Female	2.204
Dependents Status:[a]		Army Eligibility:[a]	
None	4.266	Eligible	4.369
One or more	4.813	Not Eligible	4.660

Note: ACOL values are in thousands of 1980 dollars.

[a]For first-term reenlistment decisions in Infantry CMF.

[b]For first-term reenlistment decisions in Administration CMF.

Note that the ACOLs are greater at the second-term reenlistment decision. Given our predictions of military and civilian earnings, we calculate that, for almost all the soldiers in our sample, the maximum ACOL at both the first- and second-term decision points involves a military career that lasts through 20 years of service. The first component of ACOL in equation (6), the annualized difference in military and civilian earnings over the military

career, is probably similar at the first- and second-term decision points. But the post-service income advantage of the military career is greater at the end of the second term because the discounted present value of retirement benefits is larger. Thus, ACOLs rise as the soldier's career progresses.

The differences in ACOL values across groups defined by socioeconomic characteristics is a function of the correlation between those attributes and our predictions of military and civilian compensation. For example, we find that both military and civilian earnings increase with years of education, but the civilian earnings effects are larger, causing the average ACOL to fall with additional schooling.[47] For analogous reasons ACOLs are also lower for soldiers with higher-than-average AFQT scores and faster-than-average promotion times. Thus, across all of these indicators of employee performance, we find that relative military-civilian compensation is lower for the good performers. This does not bode well for the quality of the enlisted force, where quality is measured by education, AFQT, and relative pay grade. If pay were the sole determinant of reenlistment probabilities, this pattern of relative military pay would lead to a decline in the average quality of enlisted force in the second term as compared with the first.

The differences in average ACOLs across race and gender groups are relatively small. As we find only small racial effects in our promotion time and post-service earnings analysis, most of the ACOL differences by race are caused by differences across the groups in other attributes, such as AFQT scores.[48] The small gender differences, of course, reflect our decision not to use the unreasonably large female coefficient in predicting post-service earnings. Finally, note that soldiers with dependents have higher ACOLs, a result of the greater housing allowances paid to them. Soldiers who are ineligible to reenlist, according to the Army definition, have slightly higher average ACOLs than those who are eligible.

Reenlistment Model Estimates—Infantry CMF

Table 3.8 displays the partial effects on first- and second-term infantry reenlistment probabilities of changes in the variables included in the model. Three different types of partial effects are calculated from the parameters of the model by simulating changes in reenlistment probabilities for each observation in the analysis sample and then averaging the changes.

Deltas are calculated for dummy variables and can be interpreted as the difference in reenlistment probabilities between the group represented by the dummy and the omitted group, other factors held constant. Derivatives measure the probability change associated with a unit change in the explanatory variable; elasticities, the percentage change in reenlistment probabilities for a percentage change in the variable. When the coefficient underlying the partial effect is significantly different from zero at the 5 percent level (using a two-tailed test), we mark the effect with an asterisk.

Table 3.8
Infantry Reenlistment Effects[a]

Variable	First-Term Reenlistment	Second-Term Reenlistment
Delta:		
Black	0.162*	0.101*
Hispanic	0.014	0.066
Other Minority	0.076	−0.006
Indirect Fire Infantry	−0.009	−0.017
Heavy Anti-Armor Weapon Infantry	−0.013	−0.066
Fighting Vehicle Infantry	0.009	−0.002
Post FY 1982	−0.146*	−0.006
Derivative:		
Length of Initial Term	0.091*	0.009
Education Benefits	−0.014	0.017*
Unemployment at Accession	−0.001	−0.001
Number of Dependents	0.059*	0.022*
Years of Education	−0.011*	0.035*
Eligibility Rate	0.001	0.009*
Relative Pay Grade	0.056*	0.188*
AFQT Score	−0.005*	0.005
Elasticity:		
Unemployment	−0.218	−0.478*
Military Pay	1.285*	0.857*

[a]Partial effects on probability of reenlistment. See text for details and Tables A-1 and A-2 for the underlying parameter estimates. Asterisks indicate effects that are significantly different from zero at the 5% level.

Tables A-2 and A-3 display the coefficients and associated standard errors for the infantry, mechanical maintenance, and administration models.[49] Unlike previous applications of the ACOL-2 methodology, we do *not* constrain the parameters at the first- and second-term decision points to be the same. Although this is different from the theoretical development of the model in the last chapter, we found that the constraints were not supported by the data. Likelihood ratio tests reject the constraints for all three CMFs at the 1 percent level.

In general, there are two reasons why the parameters of reenlistment decision models for the first and second term might be different. The first is the censoring of tastes for military service that occurs at the first-term decision point, but we control for the effects of censoring on the second-term parameters by jointly modeling the first- and second-term decisions in the ACOL-2 framework. The second reason for different parameters is that there may be term-specific differences in the reenlistment process. For example, the minimum grade requirement for reenlistment eligibility is less likely to be a binding constraint at the first reenlistment point than at the second. In a reduced form eligibility-reenlistment model such as ours, this means that the correlation between relative grade and reenlistment rates will vary across terms.[50]

Turning to the individual parameter estimates, we discuss the reenlistment effects of the "taste" variables, such as race, the demand-related variables, such as the eligibility rate, unemployment, and military pay in turn.

Taste Effects. Confirming the findings of other reenlistment studies for Army enlisted personnel, we find that black and, to a lesser extent, other minority soldiers are much more likely to reenlist than whites. The size of the effect at the first term—a .16 difference between blacks and whites when the mean reenlistment rate is .33—is somewhat surprising, especially given the number of other factors that are being held constant in making this comparison. In interpreting the taste effects, it is important to remember that the estimated effects are conditional on our predictions of relative military compensation. If we have underestimated the black-white earnings differential for veterans, as an example, we will overestimate the effect of taste differences between black

and white soldiers. The higher reenlistment rate for blacks persists at the second term, although the black-white difference is smaller.

Also as in previous studies, we find that soldiers with dependents are more likely to reenlist than soldiers with no dependents, holding constant the difference in relative pay due to housing allowances. The effects are substantial for members of the Infantry CMF. An additional dependent at the first-term decision is associated with a .059 increase in the reenlistment rate; at the second term, the effect is smaller, .022 per dependent.

The other taste variables in the model have plausible signs. Like Daula and Baldwin (1985), we find that soldiers who choose longer initial terms are more likely to reenlist at the end of the first term. The differences between two- and four-year enlistments for the infantry are on the order of the black-white differences, .182 higher reenlistment probabilities for the longer initial term.

We also find that soldiers who are eligible for greater education benefits are less likely to reenlist at the first-term decision point. The size of the estimated effect for the infantry is similar to that found by Hogan et al. (1990) using a single accession cohort pooled across occupations. Soldiers eligible for the ACF have education benefits that are approximately $3,000 to $4,000 higher, in discounted present value, than soldiers eligible only for VEAP (see Table C-3). This implies a first-term reenlistment rate that is .042 to .064 lower.

We hypothesized that unemployment at accession would be negatively correlated to first-term reenlistment rates through the selection process occurring at enlistment. The coefficient on unemployment at accession does have a negative sign, but the effect is small and not significantly different from zero.

Controlling for other variables, we also find no difference in reenlistment rates across the occupations in the Infantry CMF. To explore the issue of cross-MOS differences further, we also estimated the model in Table 3.8 with MOS-ACOL interactions. We found similar pay elasticities for the different occupations in the Infantry CMF and could not reject the null hypothesis of a single pay effect for the entire CMF, using a likelihood ratio test at the 5 percent level. Thus, a single model for the MOSs in the Infantry CMF is appropriate.

Demand Variables. As we noted in the last section, the coefficients on the education, AFQT, and relative grade variables combine eligibility and taste effects in our model. We can sort out the effects by comparing the results with a model estimated only for reenlistment-eligible soldiers, which we will do below. For now, note that, on net, soldiers in the Infantry CMF who have been promoted faster are more likely to reenlist, holding constant other factors.[51] A soldier who is half a grade ahead of his or her cohort at the first-term reenlistment point, which places him or her in approximately the top 15 percent in terms of promotion speed, has a reenlistment probability about .03 higher. The effect is larger at the second term. Of course, the *total* difference between the reenlistment rates of fast and slow promotees is smaller because fast promotees also have lower ACOLs and, as we will confirm, reenlistment rates are positively related to pay.

In contrast, we find that high-quality soldiers, who have more years of education and higher AFQT scores, have *lower* reenlistment rates at the first term than we would expect from relative pay differences alone. Thus, the taste effect reinforces the relative pay effect, so that the overall reenlistment rate for high-quality soldiers is lower. This means that the proportion of high-quality soldiers in the infantry drops as cohorts move through the first-term reenlistment point.

We get mixed results in the infantry model for our reenlistment management variables. Holding constant time series changes in pay, unemployment, and the quality of reenlistment cohorts, we find that first-term reenlistment rates dropped substantially in the years after FY 1982.[52] This is consistent with the effects we expected from the change in the reenlistment goal-setting process, but the magnitude of the difference—.15 when reenlistment rates average .33—suggests further exploration. (We estimate the infantry model separately for the two periods below.) Unfortunately, the eligibility rate variable, which would be much more useful for forecasting purposes than a dummy variable, is not significantly different from zero at the first term and has an unexpectedly positive sign at the second-term decision point.

Unemployment. Contrary to expectations, we find a negative relationship between unemployment and reenlistment probabilities, although the estimated coefficient is not statistically significant. Thinking that national unemployment rates

might be correlated with time-series changes not otherwise measured in the model, we also used the decision year value of the unemployment rate for the state from which the soldier accessed. As many soldiers who separate after the first term return to their accession state, this rate could be a better measure of the riskiness of civilian employment as perceived by the soldier making a reenlistment decision.[53] For the Infantry CMF, the unemployment effect became positive at the first reenlistment point, but it was small in magnitude and insignificantly different from zero.

These results are not all that different from those found in other microdata models of Army reenlistment behavior. For example, Daula and Baldwin (1986) report a small, positive unemployment elasticity for first-term reenlistment decisions. One possible explanation for the consistent finding of small unemployment effects across different studies is that the unemployment prospects of veterans, who all have occupational training and a significant amount of work experience, are simply not highly correlated with changes in aggregate unemployment rates.

Military Pay. For infantry soldiers, we find a first-term pay elasticity of 1.3 and a smaller second-term elasticity of 0.9. These elasticities are calculated by simulating, for each soldier in the sample, the reenlistment effect (in percentage terms) of a 1 percent increase in basic pay, BAS, and BAQ and then averaging the results. Thus, these elasticities can be used to evaluate the reenlistment impact of the typical military "pay" raise.[54] For example, the model predicts that a 5 percent pay raise would increase the FY 1987 first-term reenlistment rate for infantrymen by 6.5 percent, or from .30 to .32.

We also simulated the reenlistment effect of a bonus change. On average, a one-level increase in the SRB multiplier increases the first-term reenlistment rate by 2.2 percent; the second-term reenlistment rate, by 1.7 percent. Thus, increasing the reenlistment bonus by one level for first-term infantrymen in FY 1987 would increase the reenlistment rate from .30 to slightly less than .31.

How does our estimated first-term pay elasticity compare with previous results? In the specification that is closest to the model estimated here, Daula and Baldwin (1986) find essen-

tially a zero pay effect for infantry soldiers making a first-term reenlistment decision.[55] There are several methodological differences between the studies that could explain the difference in estimated pay elasticities: Baldwin and Daula assume a four-year military career horizon in calculating their relative pay variable, they estimate their model for only one infantry MOS, they use a slightly different specification of taste variables, and they base their analysis on infantrymen making reenlistment decisions between FY 1976 and FY 1980. As we will show later, the difference in the time periods in which reenlistments occur seems to be the crucial factor.

Finally, we find that 31 percent of the variance in unobserved errors affecting the first- and second-term reenlistment decisions of soldiers in the infantry is due to individual-specific tastes as opposed to transitory factors. Our estimate of ρ is not significantly different from zero (see Table A-1), but this may be due to the weaker identification of this parameter as compared to an ACOL-2 model with parameters constrained to be equal across reenlistment decisions. In the constrained model, we obtain about the same point estimate for ρ, but a smaller standard error.

Because of the individual-specific tastes, pay changes at the first-term decision point will have lagged effects, in the opposite direction, on second-term reenlistment rates. For example, an increase in the first-term reenlistment bonus induces soldiers who would not have otherwise reenlisted to do so, causing the average taste for military service and, therefore, reenlistment rates at the second term to be lower. These lagged effects, however, are relatively small. As compared with a direct bonus effect of 2.2 percent at the first term, a one-level increase in the first term SRB decreases second-term reenlistment rates by 0.3 percent.[56]

Mechanical Maintenance and Administration Results

The reenlistment effects for the Mechanical Maintenance and Administration CMFs are shown in Tables 3.9 and 3.10, respectively. Many of the results are similar across all three CMFs. For example, we find that black soldiers and soldiers from other minority groups in mechanical maintenance and administration occupations have, like their counterparts in the infantry, substantially higher reenlistment rates than white soldiers, other things equal. However, only in the Administration CMF do we find that Hispanic soldiers have higher reenlistment rates.

Table 3.9
Mechanical Maintenance Reenlistment Effects [a]

Variable	First-Term Reenlistment	Second-Term Reenlistment
Delta:		
Black	0.184*	0.085*
Hispanic	−0.006	0.069
Other Minority	0.076*	0.127*
Female	0.092*	−0.014
Weapons Repair	0.018	−0.050
Utilities, Power Repair	0.026	−0.020
Construction Equipment Repair	−0.054*	−0.128
Wheeled Vehicle Mechanic	0.001	−0.062
Tracked Vehicle Mechanic	−0.002	−0.102*
Post FY 1982	−0.085*	−0.122*
Derivatives:		
Length of Initial Term	0.068*	0.037
Education Benefits	−0.006	0.002
Unemployment at Accession	0.005*	0.008
Number of Dependents	0.051*	0.024*
Years of Education	0.012*	0.025
Eligibility Rate	0.000	−0.006
Relative Pay Grade	0.069*	0.204*
AFQT Score	0.006*	0.011
Elasticity:		
Unemployment	−0.187	−0.119
Military Pay	1.764*	1.121*

[a]Asterisks indicate effects that are significantly different from zero at the 5% level.

In both mechanical maintenance and administration, we estimate that female soldiers are more likely to reenlist at the first-term decision point than similar males. In contrast to the estimated differences across racial groups, where we adjust our predictions of post-service earnings for race, it is more likely that this effect can be explained by lower post-service earnings opportunities for female soldiers that are not captured in our ACOL

Table 3.10
Administration Reenlistment Effects[a]

Variable	First-Term Reenlistment	Second-Term Reenlistment
Delta:		
Black	0.185*	0.115*
Hispanic	0.113*	0.169*
Other Minority	0.107*	0.114*
Female	0.067*	−0.053
Administration Specialist	0.016	0.007
Personnel Specialist	0.037*	0.035
Finance/Accounting	−0.035	0.041
Legal/Court	−0.045	−0.054
Physical Activity	−0.063	−0.138
Post FY 1982	−0.080*	−0.047
Derivatives:		
Length of Initial Term	0.074*	−0.043
Education Benefits	−0.008*	0.003
Unemployment at Accession	−0.002	−0.010
Number of Dependents	0.040*	0.029*
Years of Education	−0.004	0.012
Eligibility Rate	0.003	−0.001
Relative Pay Grade	0.048*	0.196*
AFQT Score	−0.011*	0.002
Elasticity:		
Unemployment	−0.426*	0.015
Military Pay	1.900*	1.761*

[a]Asterisks indicate effects that are significantly different from zero at the 5% level.

variable. To explore male-female differences in reenlistment rates further, we also estimated separate models for male and female soldiers in the Administration CMF. At the 5 percent level, we can reject the hypothesis that the parameters of the reenlistment model are the same for male and female soldiers. There are two major differences in the results. First, male soldiers with pay grades higher than the average for their

cohorts are, like members of the infantry, more likely to reenlist. There is no difference in reenlistment rates for similar females. Second, we estimate a higher pay elasticity for males (2.7) than females (1.4).

The other variables representing taste differences generally have the same relationship to reenlistment in these CMFs as in the infantry. For example, soldiers with dependents are more likely to reenlist at the end of both the first and second terms. Soldiers who initially enlist for longer terms of service as mechanics or clerks are more likely to reenlist. Those who are eligible for greater education benefits have lower reenlistment rates, although the effect is not as pronounced as for members of the Infantry CMF. The differences in reenlistment rates across occupations within the Mechanical Maintenance and Administration CMFs are generally small; as with the infantry, we cannot reject the hypothesis that pay elasticities within a CMF are the same. For administration, we find that unemployment at accession is negatively correlated with reenlistment, but like the results for infantrymen, the correlation is not significantly different from zero. For mechanics, we get an unexpected positive correlation.

As with the infantry, we find that soldiers in mechanical maintenance and administration who have been promoted faster are more likely to reenlist, holding constant differences in relative military-civilian pay. But, unlike the infantry, there is not always a negative correlation between reenlistment probabilities and AFQT and education. In fact, both variables are positively related to reenlistment probabilities for mechanics.

The results for our reenlistment management variables are qualitatively similar to the findings for the infantry. That is, holding constant time-series changes in relative pay and unemployment, there is a substantial drop in first-term reenlistment rates after FY 1982, although the size of the decrease is not as great as for the Infantry CMF. The eligibility rate variable in these results is also insignificant.

We find that the effect of national unemployment on the reenlistment rates of mechanics is not statistically significant,

while the effect on soldiers in the Administration CMF is, unexpectedly, negative.

The estimated pay elasticities are higher for both CMFs relative to the infantry, in particular, 1.8 for mechanics at the end of their first term and 1.9 for clerks at the same point. As noted by Warner and Goldberg (1984), this result can be explained by differences in the variance of tastes for military service, the λ's, across the CMFs. As described in the last section, these tastes are a function of the difference between the nonpecuniary attributes of a military and civilian career, NC_i-NM_i. To the extent that these attributes are positively correlated in military and civilian employment, the variance of the difference in the attributes and, therefore, the variance of tastes will be smaller. But, if $\sigma^2\lambda$ is smaller, $\sigma^2\eta$ will also be smaller; and, from equation (9), the pay elasticity will be larger. In contrast to soldiers in the infantry, soldiers in both the Mechanical Maintenance and Administration CMFs are qualified for civilian jobs that have similar attributes to their military occupations. Thus, we would expect to find higher pay elasticities for these CMFs.

As with the infantry, second-term pay elasticities are smaller than the first for soldiers in mechanical maintenance. However, there is very little difference for the Administration CMF.

Finally, we note that the proportion of individual-specific tastes in the total error for these CMFs is similar to the infantry. But, also like the infantry result, the estimated ρ's are not significantly different from zero and the magnitudes of the lagged effects of compensation changes are small.

ACOL Specification Issues

There are two reasons to explore alternative specifications of the reenlistment model. First, such testing is important in understanding how much reliance should be placed on particular point estimates in making personnel policy decisions. There is already evidence—Daula and Baldwin (1986) make the strongest case—that seemingly innocuous changes in the specification of reenlistment models can produce large differences in key parameter estimates, such as the pay elasticity. Second, to the extent that testing alternative

specifications helps to explain differences in findings between studies, it also improves our understanding of how to model the reenlistment process. Given the available reference point in the work of Daula and Baldwin, we focus attention in this part of the analysis on the first-term reenlistment decision of soldiers in the infantry.

First, we examine the sensitivity of the estimated pay elasticity to four issues in the calculation of the ACOL variable:

- Different specifications of the models used to predict military and civilian compensation,
- Giving reenlistment bonuses to soldiers who would have received them if they had not opted for retraining,
- The choice of a discount rate, and
- Alternative models of expectations about the general level of relative military/civilian pay.

In addition, we also estimate the reenlistment model with a reduced form specification of civilian earnings. In theoretical terms, this specification is a more restrictive version of the ACOL model, but it offers some empirical advantages because no civilian earnings predictions are required. Table 3.11 lists the pay elasticities from these variations.

Specification of Earnings Functions. How we specify the earnings models interacts with the specification of the taste variables in the reenlistment model. For that reason, we estimate ACOL specifications one through three in two ways, using the set of taste variables in the baseline model and using a reduced set, which excludes education benefits, length of initial term, unemployment at accession, years of education, relative pay grade, and AFQT score. The latter specification, in which race and dependents are the only taste variables, has been used frequently in the retention literature.

For our baseline ACOL specification, there is very little difference between the pay elasticities when we change the specification of tastes. This is deceptive, however. If we drop just the taste variables measured at the accession point—education benefits, accession unemployment, and initial term of service—the pay elasticity rises to 3.4 from 1.3. Thus, our results do confirm the findings in Daula and Baldwin (1986),

Table 3.11
Infantry Pay Elasticities With Alternative ACOL Specifications[a]

ACOL Specification	Specification of Taste Variables: Reduced Set[b]	Variable Set
1. Baseline model	1.4*	1.3*
2. Mean promotion times used to predict military compensation instead of promotion time models	1.3*	1.7*
3. Post-service earning a function of military and civilian experience only	1.9*	1.1*
4. Soldiers reenlisting for retraining given a bonus (if available in their previous MOS)	—	2.5*
5. Alternative discount rates:		
3%	—	1.6*
10% (baseline)	—	1.3*
17%	—	0.7*
6. Rational expectations model of relative military/civilian pay level	—	0.6*
7. Model with a reduced form in post-service earnings	—	1.9*

[a]Elasticities for first-term decision. An asterisk indicates the ACOL coefficient is significantly different from zero at the 5% level.

[b]Baseline model without education benefits, initial term of service, unemployment at accession, years of education, AFQT, and relative pay grade.

who argued that one potential source of variation in pay elasticity estimates is the specification of the taste variables. On both theoretical and empirical grounds, we favor our baseline specification. In the last section, we described the theoretical reasons for including each of the taste variables in our specification. Omitting such variables potentially biases the pay elasticity. With a likelihood ratio test, we can also reject at the 5 percent level the parameter constraints implied in the reduced set model.

We experiment with two variations in predicting earnings. In specification 2, we use mean promotion times to predict military compensation instead of the promotion time models, which vary promotion speeds according to a soldier's characteristics. The post-service earnings predictions in this specification are the same as in the baseline model. In specification 3, we substitute a post-service earnings function, which only includes years of military and civilian experience for the earnings function described in the last chapter and use the military compensation predictions from the baseline model.

Look first at the models with the reduced set of taste variables. When we use mean promotion times, we reduce the military compensation of soldiers who have, for example, above-average AFQT scores and years of education (that is, are "high quality") compared with the compensation predictions for these same individuals in the baseline model. As these soldiers also have lower-than-average ACOLs (see Table 3.7), this reduces the slope of the reenlistment-ACOL relationship. Specification 3 has the opposite effect on the pay elasticity because it reduces the civilian compensation of high-quality soldiers, thereby increasing their ACOLs relative to the baseline specification.[57]

We, of course, prefer the specification of military and civilian compensation used in the baseline model. The promotion time and post-service earnings results show that it is statistically inappropriate to exclude characteristics from the compensation predictions as we did in specifications 2 and 3. The results do illustrate, however, that differences in the methodologies used to predict military and civilian compensation in the ACOL framework can have a substantial effect on the estimated pay elasticities.[58]

Assignment of the Reenlistment Bonus. Soldiers who reenlist for retraining in a new MOS generally forgo any bonus available for reenlisting in their old occupation and, therefore, in the baseline ACOL specification we do not assign a bonus to these individuals. As the opportunity cost of retraining, the forgone bonus must be less than the value of the post-service earnings returns to the new training and/or the benefits of a better lifestyle in the new MOS. If the MOS change is motivated

primarily by increased post-service earnings, it is appropriate to include the bonus in ACOL as an approximation of these additional returns because, under our assumption of continued service in the old MOS, they are not otherwise included in the post-service earnings projections. On the other hand, if the MOS change is due primarily to nonpecuniary factors, the treatment of bonuses in the baseline model is correct.

Like Daula and Baldwin (1986), we find (in specification 4) that assigning a bonus to MOS switchers produces a significantly higher infantry pay elasticity, almost doubling the baseline result at 2.5. A multiple-choice model, which allows the correct specification of the financial returns to reenlisting, retraining, and separating, is required to determine where the "true" pay elasticity lies in this range. Estimating a multiple-choice model for first- and second-term decisions is beyond the scope of this effort, but we did experiment with a simple multiple-choice specification—the independent probit described in Hausman and Wise (1978)—for first-term decisions only.[59]

Because we used a different sample and a different set of explanatory variables in this excursion, we first estimated simple probits in which reenlistment bonuses were and were not assigned to MOS switchers. We obtained pay elasticities of 1.8 and 1.1, respectively, replicating the qualitative results in Table 3.11. With the independent probit, we estimated a pay elasticity only slightly larger than in the simple probit in which bonuses were not given to switchers, 1.2. This result is consistent with MOS migration patterns reported by Daula (1981). He notes that most infantry soldiers who retrain do not opt for skill-intensive occupations but for military occupations with a better lifestyle.

Discount Rate. The baseline model assumes a discount rate of 10 percent. To test the sensitivity of our results to this assumption, we calculated ACOLs using 3 percent and 17 percent and reestimated the reenlistment model. The resulting pay elasticities range from 0.7, with a discount rate of 17 percent, to 1.6, with a 3 percent rate. A lower discount rate, besides raising the average ACOL value, gives more weight to the post-service differences in the military and civilian compensation streams, retirement pay, and the civilian earnings forgone in the exchange of military for civilian labor market experience. This reweighting has a different proportional effect on soldiers with high and low ACOLs, increasing

the reenlistment-ACOL relationship. The highest value of the likelihood function occurs at a 3 percent discount rate, although the differences in the likelihood value across the discount rates are small.

Rational Expectations of Relative Pay. The baseline model assumes, as is common in the literature, that soldiers have static expectations about the general level of military pay relative to civilian earnings. That is, aside from changes in relative pay that arise from different returns to military and civilian work experience, we assume that soldiers expect their future relative pay to be the same as at the ETS point. These expectations are inconsistent with historical experience, where relative military pay follows cycles of erosion followed by a catch-up period, as is shown in Table 3.12. A more plausible assumption is that soldiers incorporate the historical pattern of relative pay in forming their expectations about future pay, or that they have rational expectations.

Table 3.12
Relative Military/Civilian Pay Index[a]

Year	Index	Year	Index
1972	1.000	1980	0.880
1973	1.007	1981	0.888
1974	1.003	1982	0.936
1975	0.972	1983	0.922
1976	0.956	1984	0.912
1977	0.927	1985	0.908
1978	0.916	1986	0.898
1979	0.895	1987	0.894

[a]Military pay raise index relative to the Employment Cost Index.

To implement this model, we assume that relative pay expectations are generated from a simple autoregressive model of the relative pay index

(13) $$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 R_{t-2} + \varepsilon_t$$

where R is the relative pay index. The results of estimating this model are displayed in Table 3.13.[60] Using the estimated

model, we predict the relative pay index for the years following a soldier's ETS date and use these predictions to adjust the level of military compensation. Given the cyclical nature of relative pay, the effect of this adjustment is to reduce the time-series variance of the calculated ACOLs. The average ACOL in years with higher-than-average relative pay are reduced because soldiers do not expect the good times to persist; lower-than-average ACOLs are increased because a return to long-run-average relative pay levels is expected.

With rational expectations, the estimated first-term military pay elasticity decreases substantially, from 1.3 to 0.6. In interpreting this result, it is important to note that a rational expectations assumption can be incorporated into the ACOL model in a number of different ways. The results from this particular model are, therefore, more interesting as an indication of the variation that can occur in the pay elasticity with different assumptions about expectations than as an estimate of the "true" elasticity.

Table 3.13
Relative Military/Civilian Pay Model

Variable	Coefficient	Std Error
Constant	0.226	0.017
R_{t-1}	0.976	0.264
R_{t-2}	−0.226	0.246

[a]OLS estimates using relative pay index in Table 3.12.

Reduced Form Civilian Earnings Specification. A reenlistment model with a reduced form specification of post-service earnings can be developed from the ACOL model found in equations (6) and (10) by assuming a constant (real) value for post-service earnings. Under this assumption, the ACOL decision rule becomes: Reenlist if

$$(14) \qquad \frac{\left(\sum_{1}^{s} WM_{it}d^{t} + \sum_{s+1}^{T} R_{st}d^{t}\right)}{\sum_{1}^{s} d^{t}} - WC_i + X_i\,\delta > \lambda_i + \varepsilon_{in}$$

where the ratio on the left side of the inequality is discounted present value of military compensation annualized over the horizon s. We substitute a reduced form expression for WC—all the variables used to predict post-service earnings plus a civilian real wage index—and estimate the resulting model assuming a military career that lasts through YOS 20. The complete results for the model are found in Appendix A.

From a theoretical perspective, the major problem with this specification is that the appropriate horizon for evaluating military compensation is no longer determined by the data. However, the estimated parameters of the model are not subject to sample selection bias in the post-service earnings predictions because no model is used to predict those earnings.[61] It is, therefore, a useful check on the results from our baseline model.

Selection bias causes us to overstate the coefficients on variables that are positively related to reenlistment and understate the parameters of variables that have a negative correlation with reenlistment.[62] This means that we will overestimate post-service earnings, and underestimate ACOLs, for soldiers likely to reenlist. The impact, then, of sample selection bias in the post-service earnings models is to reduce the estimated pay elasticity. Daula and Baldwin (1986) found that the first-term infantry pay elasticity was higher when they corrected for selection bias in a structural model of reenlistment and post-service earnings. Our reduced form model is not as clear a test, but we also estimate a higher pay elasticity for first-term infantry reenlistment decisions, 1.9.

How should we interpret the results of these specification tests? We have already argued that the baseline model dominates the specifications that omit taste and/or earnings variables because of the potential for bias in these specifications. If our preliminary estimates of the reenlist-retrain-separate model are indicative, correctly modeling the retraining choice would not significantly alter the pay elasticity obtained in the baseline model. There is weak evidence in the data for using a lower discount rate, but doing so would only increase the pay elasticity modestly. The two remaining issues—the expectations assumption and selection bias in post-service earnings—cannot be so easily dismissed because of their relatively large effects on the estimated pay elasticity. Fur-

ther research on both issues is clearly needed. Until there is more empirical evidence, however, the pay elasticity from the baseline model seems to lie in a reasonable middle ground.

Demand Factors in the Reenlistment Model

In the model specification section, we identified two ways in which Army demand affects the reenlistment decisions of soldiers—through reenlistment eligibility and by managing aspects of the reenlistment process such as reenlistment goals. To isolate the voluntary aspects of the reenlistment decision, we included, as controls for Army demand, both performance-related soldier characteristics and variables potentially correlated with the reenlistment management process.

An alternative approach is to limit the samples for the reenlistment model to soldiers who, because of their superior performance, would not be affected by demand constraints.[63] To test this approach, we estimate models of the first-term reenlistment decision for two subgroups of the infantry—soldiers who are eligible to reenlist according to the Army definition and high-quality soldiers. In addition, because of the substantial difference between reenlistment rates before and after FY 1983, we estimate separate models for each period. Selected results from these models are displayed in Table 3.14. The corresponding results from the all-at-ETS sample used to estimate the baseline model are also included for comparison purposes. Complete results for these models can be found in Appendix A.[64]

Look first at the results across samples. Conditioning on reenlistment eligibility or high quality does not significantly change the estimated first-term military pay elasticity in either period. This is the result we would expect if we have adequately controlled for demand differences across soldiers with different characteristics.[65]

There are, however, striking differences across the two periods. First, high-quality soldiers and those who have been promoted faster are more likely to reenlist in years after FY 1982, holding constant pay differences. For example, before 1983, the soldier a full grade ahead of his or her accession cohort had a reenlistment rate 3 percentage points *lower* in the all-at-ETS sample; after 1982, the reenlistment rate is over 13 percentage points *higher*.

Table 3.14
First-Term Infantry Effects, by Sample and Fiscal Year [a]

Variable	All-at-ETS	Army Eligibles Only	High-Quality Soldiers Only
Decisions in FY76–82:			
Years of Education	–.036*	–.055*	–.014
AFQT Score	–.013*	–.020*	–.010
Relative Pay Grade	–.033*	–.091*	–.036
Eligibility Rate	.013	.008	.018
Unemployment Elasticity	.479*	.371*	.501
Military Pay Elasticity	–.627	–.593	.380
Reenlistment Rate	.383	.482	.315
Sample Size	11,067	8,781	3,378
Decisions in FY83–87:			
Years of Education	.010	.001	.010
AFQT Score	.005	.003	–.006
Relative Pay Grade	.134*	.078*	.076*
Eligibility Rate	–.003	–.004*	.001
Unemployment Elasticity	–.800*	–.633*	.200
Military Pay Elasticity	3.61*	2.99*	3.34*
Reenlistment Rate	.286	.350	.235
Sample Size	11,779	9,608	3,942

[a] Asterisks indicate that the underlying coefficient is significantly different from zero at the 5% level.

This difference seems to be due to a change in tastes, not stricter eligibility requirements. Among soldiers who are eligible to reenlist, we observe a similar 17 percentage point swing in the reenlistment effect associated with relative grade. One explana-

tion for this shift in tastes is the improved environment for being a Noncommissioned Officer (NCO) after 1982. Starting in FY 1981, the quality of new accessions started to rise, so that a high-quality NCO could increasingly expect to work with similarly talented and motivated soldiers in the junior grades. In addition, the Army embarked on a force modernization program, allowing soldiers to work with up-to-date weapons systems.

Second, when we estimate separate reenlistment models for the latter period, evidence of reenlistment management policies operating on the pool of reenlistment-eligible soldiers also appears. In the model estimated with eligibles only, we find that soldiers with the same financial opportunities and taste-related attributes are less likely to reenlist when the quality of the reenlistment cohort, as measured by the aggregate eligibility rate, is high. This suggests that there were queues for reenlistment in the latter period that did not exist before 1983.

We also find very different unemployment and pay elasticities in the two periods. There is a small, positive unemployment effect and a statistically zero pay elasticity for the infantry reenlistment decision between FY 1976 and FY 1982. In the latter years, however, there is a negative unemployment effect and a pay elasticity that is unexpectedly large given the estimate in the baseline model. These results have both reassuring and disquieting aspects. Given the careful and exhaustive analysis of Daula and Baldwin, it is comforting to obtain results similar to theirs over approximately the same time period. The disquieting aspect, of course, is that the pay elasticity estimates are so volatile.

We believe that the volatility is related to the identification of the pay effect in our models. With theoretical justification, we have included in the model a rich set of variables to capture taste differences between soldiers making reenlistment decisions. As we have noted, this specification is the source of the relative stability we find in our pay elasticity estimates across different samples and, to a lesser extent, across variations in the assumptions used to calculate the ACOL variable.

However, by including as taste variables many of the characteristics also used to predict military and civilian com-

pensation, our estimates rely more heavily on time series variation to identify the effect of relative pay on reenlistment behavior. One can argue that, in principle, it is better to allow time series changes in relative pay to weigh more heavily in the estimation of the pay effect for it is the effects of these changes that are of most interest to policymakers. But, it does mean that pay elasticities estimated with a short time series, such as the five years in the latter period, are subject to the same variability one would expect in any small sample estimates. Therefore, as far as the pay elasticity is concerned in our model, we believe that the full sample estimates are more reliable.

Summary of Findings

In this section, we presented the results of estimating reenlistment models for the Infantry, Mechanical Maintenance, and Administration CMFs. We will summarize our findings in terms of military pay effects, the sensitivity of those estimates to assumptions used in calculating the ACOL variable, unemployment effects, the relationship between reenlistment and the taste variables included in the model, and the influence of demand factors on reenlistment behavior. Research and policy implications are discussed along with the findings.

Military Pay. The central results on the effects of military compensation on reenlistment rates include the following:

- We estimate that the elasticity of the reenlistment rate with respect to an increase in basic pay, BAS, and BAQ—the typical military "pay" raise—is 1.3 for first-term infantry soldiers. The military pay elasticity at the second-term decision point is smaller, 0.9.
- A one-level increase in the Selective Reenlistment Bonus is estimated to increase first-term infantry reenlistment rates by 2.2 percent; second-term rates, by 1.7 percent.
- The estimated military pay elasticities vary across CMFs. As we would expect, given the similarities between military and civilian jobs in these occupations, soldiers in mechanical maintenance and administration have higher military pay elasticities

than the infantry. At the first term, we estimate a pay elasticity of 1.8 for mechanics and 1.9 for soldiers in the Administration CMF.

- For all the CMFs, we find no statistically significant differences in military pay elasticities across the component MOSs of a CMF. This means that, for these CMFs at least, CMF-level pay elasticities are appropriate for policymaking purposes.
- In the Administration CMF, which has the greatest proportion of female soldiers among the three CMFs studied, we find significantly higher pay elasticities for males than for females. This difference, however, is sensitive to our assumptions about the male-female differential in post-service earnings.

ACOL Assumptions. Testing the sensitivity of the estimated pay elasticities to the assumptions used in calculating the ACOL is an important step in evaluating the usefulness of the reenlistment model for policy purposes. We examine five issues using the Infantry CMF:

- The estimated pay elasticities are sensitive to the joint specification of two sets of variables: those in the earnings functions and those included to capture differences in tastes for military service. Because of the potential for bias when key variables are omitted, we prefer the relatively rich specifications found in our baseline model.
- In a reenlist-separate model, there are theoretical arguments for and against the assignment of reenlistment bonuses to soldiers who reenlist for retraining in a different MOS. We find that the way bonuses are assigned has a significant impact on the estimated pay elasticity. Preliminary estimates of a multiple-choice model, in which the compensation associated with each option can be correctly represented, suggest that *not* assigning bonuses in a reenlist-separate model is the best approach.
- A discount rate must be selected to calculate ACOL, and the choice does affect the estimated pay elasticity. Following most of the literature, our baseline

model assumes a 10 percent real discount rate. There is weak statistical evidence, however, that a lower discount rate, which yields a slightly higher pay elasticity than that obtained in the baseline model, is more appropriate.

- Our baseline model assumes that soldiers have static expectations about future levels of relative military pay. We also estimated a rational expectations model in which extremely high or low levels of relative pay at the decision point are assumed to trend back to the long-run average. In this model, we find a pay elasticity substantially lower than in the baseline model.
- The usual formulation of the ACOL model requires predictions of post-service earnings, which are potentially subject to sample selection bias. A sample selection correction cannot be easily implemented given the available data, but we did estimate a modified ACOL model in which post-service earnings are expressed as a reduced form of soldier characteristics, eliminating the need for an earnings model. As expected from theoretical considerations, we find a higher pay elasticity than in our baseline model.

The estimated pay elasticity from the baseline model stands up reasonably well under these tests. Changing the discount rate and correctly modeling the retraining choice seem to have only modest effects on the estimated pay elasticity. In contrast, the particular model of expectations formation assumed and adjusting for sample selection bias in post-service earnings models have substantial effects. However, because the effects are in opposite directions, the pay elasticity from the baseline model cannot be characterized as definitely too low or too high.

Our analysis of the effects of ACOL assumptions on the estimated military pay elasticity also highlights several issues that could benefit from additional research. First, further exploration of the effects of changing the expectations model seems warranted. A broader survey could determine whether the results obtained here are atypical. The second issue is the

appropriate discount rate to use in calculating ACOLs. A retention model that incorporates the discount rate as an explicit parameter to be estimated and/or studies of natural experiments where soldiers can opt for different time patterns of compensation could narrow the uncertainty over the discount rate. Third, better models of post-service earnings are needed. Here the major roadblock is the lack of data allowing estimation of post-service earnings models that correct for sample selection bias.

Unemployment. Civilian earnings are inherently more variable than military earnings because of unemployment in the civilian labor market. To measure the impact of unemployment on the reenlistment behavior, we included the age-specific national unemployment rate at the decision point but, generally, did *not* find the expected positive correlation between the level of unemployment and reenlistment rates. While aggregate data studies of reenlistment usually find a sizeable unemployment effect, the evidence in microdata studies of Army reenlistments, such as this one, is typically more mixed.

Taste Variables. We obtain the expected results for the taste variables most commonly included in reenlistment models:

- Holding constant relative military-civilian pay, we find that black soldiers and, to a lesser extent, soldiers in other minority groups are significantly more likely to reenlist than whites.
- We also estimate that soldiers with dependents have higher reenlistment rates than would be expected from the relative pay differences alone.

These results are consistent across the three CMFs.

Reenlistment rates also vary with the choices made at enlistment into the Army:

- Not surprisingly, we find that soldiers who opt for a longer initial enlistment are more likely to reenlist, other things equal, when that term ends.

- In addition, soldiers who are eligible to receive more education benefits have lower reenlistment rates, other factors held constant.

In general, we do not find that reenlistment rates vary with the unemployment rate at accession, a potential measure of variation in the average taste for military service among different entry cohorts.

From the correlation between soldiers' first- and second-term reenlistment decisions in the ACOL-2 model, we estimate that approximately one-third of the total variation in unmeasured factors associated with those decisions was due to the variation in individual-specific tastes for military service. The presence of these tastes means that changes in military compensation at the first term will have lagged effects on reenlistment rates at the second term, although these effects are small compared to the direct effects of compensation changes.

Demand Factors. Over the period of our analysis, the Army became increasingly active in directly managing both the quantity and average quality of reenlistments. To explore the effect of Army demand in the reenlistment process, we estimated first-term infantry models with subsamples that included "desirable" soldiers only and divided the decisions into those occurring up to and after FY 1982. The results from this analysis include the following:

- Soldiers may be ineligible to reenlist for reasons that are either related or unrelated to the desire to reenlist. Only the latter cases should be excluded in estimating a model of voluntary reenlistment behavior, but data limitations make this difficult. One approach, which we use in the baseline model, is to include *all* soldiers reaching ETS in the estimation sample but also add performance-related characteristics such as AFQT, education, and relative grade to the specification. The alternative is to condition the reenlistment models on reported eligibility or eligibility-related characteristics. When we limit the estimation sample to reenlistment-eligible soldiers or high-quality soldiers, we obtain pay elasticities that are similar to the baseline model.

- Controlling for relative pay, unemployment, and the characteristics of reenlistment cohorts, we find that reenlistment rates were substantially lower after FY 1982 than before. This result is consistent with changes in the way reenlistment goals, a management tool, were interpreted.
- There was also a major shift between the periods in the propensity of soldiers with superior performance to reenlist. Before FY 1983, high-quality soldiers and individuals promoted faster than their accession cohort were actually less likely to reenlist, holding constant differences in relative pay. After FY 1982, there was no difference between the reenlistment rates of high-quality soldiers and others, and fast promotees were significantly more likely to reenlist. The statistical evidence suggests that tastes for an Army career changed between the periods, which is consistent with the improving environment for enlisted personnel across the periods.

Although we can identify the effect of changing reenlistment management policies in the reenlistment process, we did not develop a model that could forecast how changes in specific policies, such as reenlistment goals, would affect the quantity and quality of the reenlistments obtained. As the Army's sophistication in managing the reenlistment process increases, this will become an important area for future research.

Acknowledgments

We are indebted to a number of individuals for their help in preparing this chapter. Through their insights on the critical issues of Army enlisted personnel policy, Curtis L. Gilroy, David K. Horne, and Roy D. Nord of the Army Research Institute helped us define the focus for the analysis. They also provided access to data sources and institutional information that were instrumental in the completion of the work.

This study uses a new data file that was created for the project through the efforts of individuals in two organizations. Mike Dove, Monte Kingsley, and Robert Hamilton of the Defense Manpower Data Center provided the personnel records necessary to create longitudinal records tracing over

450,000 enlisted personnel from accession through separation. They were also generous in sharing with us their detailed knowledge about the files maintained by DMDC. Diane Younkman and Andrea McCarley of Fu Associates constructed the data base from the records provided by DMDC and other sources, resolving the inconsistencies that inevitably arise in data collected over a long time period.

We also received assistance from several individuals in the preliminary analysis of data sets used to model military and civilian compensation. Frank Stafford and Charles Brown of the University of Michigan took the lead in estimating post-service earnings models; our analysis is based on the findings from their initial exploration of the data. Margaret Barton and Marjorie Goon of SRA constructed the data sets and performed the preliminary analysis of promotion times, which we use in predicting military compensation. Paul Hogan and Carol Chin of SRA developed the initial algorithm for calculating the ACOL.

Finally, we would like to thank other participants in the Prototype Army Compensation Models Project for their useful comments and suggestions on our preliminary findings, especially Thomas V. Daula of the U.S. Military Academy, John Warner of Clemson University, and Matthew Black and Paul Hogan of SRA. Any remaining errors are, of course, our responsibility.

Appendix A: Supplementary Tables

Table A-1
First-Term Means by Fiscal Years

	Fiscal Year											
	76	77	78	79	80	81	82	83	84	85	86	87
Infantry:												
White	0.513	0.665	0.704	0.646	0.588	0.520	0.544	0.602	0.652	0.715	0.750	0.739
Black	0.304	0.189	0.196	0.231	0.285	0.354	0.318	0.260	0.230	0.190	0.173	0.176
Hispanic	0.157	0.100	0.051	0.071	0.090	0.086	0.081	0.065	0.053	0.052	0.043	0.045
Other Minority	0.026	0.046	0.049	0.053	0.037	0.040	0.057	0.073	0.064	0.043	0.034	0.040
Female	—	—	—	—	—	—	—	—	—	—	—	—
Initial Term	2.0	2.8	3.5	3.4	3.4	3.6	3.4	3.2	3.3	3.3	3.4	3.5
AFQT	33.9	48.7	54.8	48.8	43.3	40.4	37.9	34.8	41.7	48.1	51.4	51.0
Education Benefits[a]	8.863	8.729	8.772	9.288	6.968	4.299	2.390	2.238	2.465	2.940	3.160	3.183
Dependents	0.27	0.39	0.56	0.52	0.54	0.47	0.44	0.44	0.47	0.51	0.55	0.54
Education Years	11.0	11.2	11.8	11.6	11.6	11.8	11.7	11.3	11.8	12.0	12.1	12.1
Eligibility Rate	72.2	77.0	82.4	76.5	76.0	81.3	80.5	70.2	76.5	83.7	87.8	86.1
Reenlistment Rate	0.133	0.229	0.306	0.297	0.404	0.466	0.480	0.283	0.291	0.258	0.293	0.302
ACOL[a]	3.340	3.317	3.374	3.224	3.085	4.690	5.683	5.251	5.222	4.880	4.640	4.227
Sample Size	115	904	1037	2239	2622	1985	2274	2893	2140	2146	2392	2380
Mechanical Maintenance:												
White	0.612	0.744	0.819	0.788	0.728	0.701	0.651	0.649	0.650	0.734	0.753	0.738
Black	0.273	0.183	0.122	0.125	0.167	0.208	0.256	0.247	0.244	0.196	0.168	0.195

Table A-1 (continued)

	Fiscal Year											
	76	77	78	79	80	81	82	83	84	85	86	87
Hispanic	0.101	0.057	0.026	0.052	0.064	0.052	0.050	0.050	0.053	0.030	0.036	0.035
Other Minority	0.014	0.016	0.033	0.036	0.041	0.039	0.044	0.055	0.053	0.040	0.043	0.033
Female	0.007	0.015	0.030	0.036	0.030	0.037	0.031	0.031	0.052	0.032	0.033	0.042
Initial Term	2.0	2.9	3.0	3.2	3.3	3.6	3.5	3.5	3.6	3.5	3.4	3.6
AFQT	39.4	48.5	54.1	50.7	41.5	38.5	36.0	33.7	34.7	40.1	44.2	44.7
Education Benefits[a]	8.901	8.791	8.771	9.479	6.647	4.068	2.392	2.276	2.105	2.045	2.018	2.036
Dependents	0.28	0.61	0.59	0.55	0.58	0.46	0.44	0.51	0.56	0.59	0.63	0.68
Education Years	11.1	11.4	11.7	11.5	11.5	11.7	11.7	11.6	11.7	11.9	12.0	12.0
Eligibility Rate	79.1	80.1	85.8	74.2	70.2	75.8	75.9	73.1	76.0	83.4	87.9	85.8
Reenlistment Rate	0.165	0.248	0.226	0.267	0.314	0.387	0.378	0.325	0.301	0.312	0.327	0.376
ACOL[a]	2.440	2.313	2.417	2.512	2.491	3.712	4.823	4.751	4.701	4.258	4.023	3.627
Sample Size	139	1375	696	1320	2531	1962	1534	2201	1843	1840	1773	2080
Administration:												
White	0.463	0.492	0.545	0.456	0.395	0.399	0.407	0.366	0.420	0.428	0.464	0.448
Black	0.379	0.400	0.389	0.462	0.493	0.510	0.497	0.526	0.472	0.482	0.428	0.452
Hispanic	0.084	0.064	0.022	0.045	0.059	0.046	0.046	0.042	0.044	0.039	0.058	0.053
Other Minority	0.074	0.043	0.045	0.036	0.053	0.044	0.050	0.066	0.063	0.052	0.050	0.048
Female	0.232	0.339	0.304	0.431	0.358	0.309	0.562	0.475	0.396	0.406	0.418	0.464
Initial Term	2.0	2.9	3.0	3.1	3.3	3.3	3.5	3.4	3.2	3.2	3.1	3.2

Table A-1 (continued)

	Fiscal Year											
	76	77	78	79	80	81	82	83	84	85	86	87
AFQT	52.4	60.2	59.4	55.5	46.0	46.3	45.7	41.7	47.3	49.4	53.4	53.3
Education Benefits[a]	8.854	8.766	8.770	9.414	7.180	4.045	2.630	2.234	2.425	2.801	3.426	3.197
Dependents	0.37	0.49	0.57	0.48	0.50	0.49	0.45	0.43	0.52	0.59	0.51	0.56
Education Years	12.1	12.2	12.3	12.3	12.2	12.3	12.4	12.3	12.3	12.4	12.5	12.4
Eligibility Rate	69.5	78.0	87.7	87.0	81.8	81.5	85.3	84.6	85.2	89.0	90.4	87.9
Reenlistment Rate	0.116	0.316	0.358	0.408	0.457	0.516	0.541	0.484	0.410	0.455	0.439	0.460
ACOL[a]	2.245	2.748	2.832	3.178	2.680	3.656	5.901	5.172	4.643	4.558	4.576	4.453
Sample Size	95	924	674	662	1381	1149	883	952	1192	1319	1266	1025

[a]In thousands of dollars.

Table A-2
***First-Term Reenlistment Parameter Estimates*[a]**

	Career Management Field		
Variable	**Infantry**	**Mechanics**	**Adminis-tration**
Intercept	–1.098 (0.291)[b]	–1.994 (0.349)	–1.400 (0.484)
Black	0.431 (0.026)	0.493 (0.031)	0.490 (0.030)
Hispanic	0.039 (0.043)	0.018 (0.056)	0.303 (0.059)
Other Minority	0.206 (0.048)	0.210 (0.059)	0.289 (0.058)
Female	— —	0.254 (0.063)	0.183 (0.025)
Length of Initial Term	0.268 (0.022)	0.199 (0.027)	0.201 (0.032)
AFQT Score	–0.014 (0.006)	0.019 (0.009)	–0.031 (0.007)
Education Benefits	–0.041 (0.005)	–0.017 (0.006)	–0.023 (0.006)
Unemployment at Accession	–0.003 (0.006)	0.014 (0.006)	–0.007 (0.006)
Number of Dependents	0.175 (0.012)	0.151 (0.014)	0.110 (0.016)
MOS1[c]	–0.025 (0.027)	0.052 (0.055)	0.045 (0.047)
MOS2	–0.035 (0.038)	0.075 (0.048)	0.101 (0.049)
MOS3	0.025 (0.076)	–0.161 (0.061)	–0.102 (0.061)
MOS4	— —	0.003 (0.040)	–0.130 (0.096)
MOS5	— —	–0.007 (0.043)	–0.184 (0.137)
Relative Pay Grade	0.166 (0.029)	0.203 (0.044)	0.131 (0.049)
Years of Education	–0.032 (0.013)	0.035 (0.018)	0.011 (0.017)

Table A-2 (continued)

	Career Management Field		
Variable	**Infantry**	**Mechanics**	**Adminis-tration**
Eligibility Rate	0.004 (0.003)	0.001 (0.003)	0.008 (0.006)
National Unemployment	–0.017 (0.010)	–0.014 (0.011)	–0.040 (0.013)
Post FY 1982	–0.446 (0.030)	–0.263 (0.036)	–0.238 (0.038)
ACOL	0.070 (0.019)	0.096 (0.024)	0.131 (0.029)
ρ	0.311 (0.232)	0.247 (0.272)	0.199 (0.297)

[a]Bivariate probit models of first- and second-term reenlistment decisions. See Table A-3 for second-term parameters.

[b]Asymptotic standard errors are in parentheses.

[c]The MOS variables are

	Infantry	Mechanics	Administration
MOS1=	Indirect Fire (11C)	Weapons Repair (45B–45Z)	Administration Specialist (71L)
MOS2=	Heavy Anti-Armor Weapon (11H)	Utilities, Power Repair (52A–52F)	Personnel Specialist (75B–75F)
MOS3=	Fighting Vehicle (11M)	Construction Equipment Repair (62B)	Finance/ Accounting (73)
MOS4=		Wheeled Vehicle Mechanic (63B, 63S, 63W)	Legal/Court (71D, 71E)
MOS5=		Tracked Vehicle Mechanic (63D, 63E, 63G, 63H, 63J, 63N, 63R, 63T, 63Y)	Physical Activity (73C)
Omitted Group=	Infantryman (11B)	Machine Repairer/ Machinist (41C, 41J, 44B, 44E)	Executive/ Chaplain Assistant (71C, 71M)

Table A-3
***Second-Term Reenlistment Parameter Estimates*[a]**

	Career Management Field		
Variable	**Infantry**	**Mechanics**	**Adminis-tration**
Intercept	–3.634 (1.050)	–0.425 (1.357)	–0.370 (0.837)
Black	0.384 (0.091)	0.355 (0.106)	0.399 (0.108)
Hispanic	0.198 (0.136)	0.211 (0.135)	0.555 (0.158)
Other Minority	0.027 (0.155)	0.458 (0.146)	0.369 (0.144)
Female	— —	0.005 (0.182)	–0.115 (0.072)
Length of Initial Term	0.083 (0.077)	0.134 (0.072)	–0.099 (0.094)
AFQT Score	0.011 (0.017)	0.032 (0.018)	0.001 (0.016)
Education Benefits	0.039 (0.015)	0.002 (0.011)	0.006 (0.013)
Unemployment at Accession	–0.004 (0.020)	0.023 (0.018)	–0.030 (0.017)
Number of Dependents	0.064 (0.028)	0.063 (0.029)	0.083 (0.029)
MOS1	–0.046 (0.081)	–0.141 (0.179)	0.019 (0.152)
MOS2	–0.181 (0.099)	–0.057 (0.159)	0.096 (0.148)
MOS3	–0.005 (0.169)	–0.353 (0.182)	0.113 (0.173)
MOS4	— —	–0.176 (0.127)	–0.146 (0.216)
MOS5	— —	–0.284 (0.135)	–0.366 (0.393)
Relative Pay Grade	0.540 (0.055)	0.541 (0.064)	0.569 (0.064)
Years of Education	0.101 (0.045)	0.067 (0.050)	0.036 (0.032)

Table A-3 (continued)

	Career Management Field		
Variable	**Infantry**	**Mechanics**	**Adminis-tration**
Eligibility Rate	0.025	–0.017	–0.003
	(0.012)	(0.014)	(0.008)
National Unemployment	–0.098	–0.022	0.004
	(0.032)	(0.026)	(0.028)
Post FY 1982	–0.016	–0.335	–0.126
	(0.145)	(0.134)	(0.095)
ACOL	0.069	0.082	0.175
	(0.033)	(0.035)	(0.035)

[a]See notes to Table A-2.

Table A-4
***First-Term Infantry Reenlistment Effects, FY76–82*[a]**

	All at ETS	Army Eligibles Only	High Quality Only
Reenlistment Rate	0.383	0.482	0.315
Partial Effects:			
Black	0.131*	0.162*	0.175*
Hispanic	–0.014	–0.021	–0.049
Other Minority	0.073*	0.086*	–0.040
MOS1[b]	0.014	0.022	0.007
MOS2	–0.040*	–0.049*	–0.068
Length of Initial Term	0.116*	0.101*	0.101*
Education Benefits	–0.012*	–0.017*	–0.005
Unemployment at Accession	0.003	0.004	–0.001
Number of Dependents	0.061*	0.070*	0.066*
Years of Education	–0.036*	–0.055*	–0.014
Eligibility Rate	0.005	0.003	0.006
Relative Pay Grade	–0.033*	–0.091*	–0.036
AFQT Score	–0.013*	–0.019*	–0.010
Unemployment Elasticity	0.479*	0.371*	0.501
Military Pay Elasticity	–0.627	–0.593	0.380
Sample Size	11,067	8,781	3,378

[a]Asterisks indicate effects that are significantly different from zero at the 5% level.

[b]See Table A-2 for definitions. MOS3, Fighting Vehicle (11M) did not exist in this period.

Table A-5
First-Term Infantry Reenlistment Effects, FY83–87[a]

	All at ETS	Army Eligibles Only	High Quality Only
Reenlistment Rate	0.286	0.350	0.235
Partial Effects:			
Black	0.162*	0.208*	0.187*
Hispanic	0.053*	0.060*	–0.050
Other Minority	0.077*	0.081*	0.030
MOS1[b]	–0.028*	–0.035*	–0.027
MOS2	–0.010	–0.019	–0.041*
MOS3	–0.010	–0.005	–0.027
Length of Initial Term	0.054*	0.065*	0.062*
Education Benefits	–0.021*	–0.024*	–0.012*
Unemployment at Accession	–0.002	–0.003	–0.003
Number of Dependents	0.053*	0.067*	0.061*
Years of Education	0.010	0.000	0.010
Eligibility Rate	0.000	–0.004*	0.001
Relative Pay Grade	0.134*	0.078*	0.076*
AFQT Score	0.004	0.003	–0.006
Unemployment Elasticity	–0.800*	–0.633*	0.200
Military Pay Elasticity	0.361*	2.986*	3.335*
Sample Size	11,779	9,608	3,942

[a]Asterisks indicate effects that are significantly different from zero at the 5% level.

[b]See Table A-2 for definitions.

Table A-6
Infantry Reenlistment Effects With a Reduced Form Specification of Civilian Earnings[a]

	First Term	Second Term
Partial Effects:		
Black	0.164*	0.073*
Hispanic	0.036*	0.004
Other Minority	0.073*	0.049
MOS1[b]	–0.012	–0.002
MOS2	–0.027	–0.006
MOS3	–0.004	0.029
Post FY 1982	–0.157*	–0.096
Length of Initial Term	0.069*	–0.013
Education Benefits	–0.013*	0.011
Unemployment at Accession	–0.000	–0.005
Number of Dependents	0.051*	0.017
Years of Education	–0.024*	0.010
Eligibility Rate	0.001	0.003
Relative Pay Grade	0.003	0.134*
AFQT Score	–0.010*	0.003
Civilian Real Wage Index[c]	–0.358	0.801
Unemployment Elasticity	–0.243	0.101
Military Pay Elasticity	1.857*	1.006*

[a]Estimated with the same sample as the baseline model (Tables A-2 and A-3). See text for details of model specification. Asterisks indicate effects that are significantly different from zero at the 5% level.

[b]See Table A-2 for definitions.

[c]Constructed from CPS earnings data for all workers and GNP deflator.

Appendix B: Enlisted Panel Research Data Base

The Enlisted Panel Research Data Base (EPRDB) is the primary analysis file used to estimate our promotion time and reenlistment models. This appendix describes the construction of the EPRDB and lists the variables contained in it.

Data Base Construction

The Defense Manpower Data Center (DMDC) compiled the primary elements for the data set through a four-step process. First, a 25% sample of all accessions that occurred during the period FY 1974–84 was drawn from the enlisted cohort files, using every fourth record from each year. These files contributed Social Security numbers and accession characteristics, such as entry date or demographic attributes, to the analysis data base. Second, these individuals were tracked through their Army career by matching Social Security numbers with the fiscal year-end Enlisted Master Files (EMFs) through either FY 1987 or separation from the Army.[66] The EMF provided time-varying data on personal and occupational characteristics, such as current Military Occupation Specialty (MOS), pay grade, and dependents status. Third, data from the Enlisted Loss Files were appended to the analysis data base for soldiers who separated from the Army. Fourth, composite test scores, such as the Combat Arms and General Technical scores, were calculated from the raw scores of the Armed Services Vocational Aptitude Battery (ASVAB).

Fu Associates created longitudinal records for individual soldiers from the DMDC data. They also resolved inconsistencies, such as separations followed by additional master file records, and updated some missing data fields. For example, AFQT was not present on all accession records but could often be found on the annual EMF records. Fu Associates also merged data from two other sources onto the analysis data base. The first set of additional data was provided by the U.S. Army Personnel Command (PERSCOM) from their Enlisted Master Files. It contained pay, demographic, and occupational data not normally deposited with DMDC. The second set of

data, provided by the SQT Directorate at Fort Eustis, contained scores from the Skill Qualifications Tests (SQT). The SQT and PERSCOM data are only available beginning in FY 1980 and FY 1984, respectively.

Variable List

The following is a list of the variables available on the EPRDB.[67]

Accession Data:

Social Security Number
Date of Birth
Sex
Race and Ethnic Group
Marital Status
Number of Dependents
Highest Year of Education
Home of Record (State, County)
AFEES/MEPS
Date of Entry
Date of Entry into DEP
Prior Service
Enlistment Term
Entry Pay Grade
Programs Enlisted For
Enlistment Bonus Option
Enlistment Special Option
Training MOS and Skill Identifier
PULHES
Accession Waiver
AFQT (Test Form, Group, Score)
Aptitude Areas
Composite Test Scores

Annual Occupation-related Data:

DoD Primary and Duty Occupation Codes
Primary MOS and Skill Identifier
Duty MOS and Skill Identifier
Career Management Field
Base Active Service Date
Pay Entry Base Date
ETS Date
Date of Rank

Date of Latest Reenlistment
Pay Grade
Force Component
SRB Multiplier
Unit Identification and Zip Codes
Character of Service
Reenlistment Eligibility
Interservice Separation Code
Date of Separation

Annual Personal Data:

Citizenship Status
Second Language
Marital Status
Number of Dependents
Exceptional Family Member Program
Highest Year of Education
SQT (MOS, Skill Level, Version, Score)
General Technical Score
Date of Last Vocational Test
NCO Education Program
Date Last Departed Overseas
Date Eligible to Return from Overseas
Date of Last PCS
Enlistment Option Code
Term of Service
Number of Times Reenlisted
Special Pay Eligibility
Proficiency Pay Status
Current Promotion Points and Date
Previous Promotion Points and Date

Appendix C: Military Compensation Predictions

Military compensation for enlisted personnel includes payments received while on active duty, such as basic pay and housing allowances, and compensation deferred until separation, such as retirement benefits. The components of military compensation have the common feature that they are all exact functions of a soldier's characteristics, such as years of service or pay grade. This means that if the relevant characteristics are known or can be predicted, military compensation can be directly calculated by looking up each component in the appropriate compensation table and adding the components. This is the approach we will take here to predict a soldier's future military compensation.

The alternative, and more common, approach is to estimate military compensation functions that are similar to the earnings functions found in the labor economics literature. However, there are two advantages to building up military compensation from its components. First, it is more accurate to use the compensation tables directly rather than trying to implicitly model the structure of the tables in a regression. The elements of military compensation are not simple functions of soldier characteristics, as the regression approach assumes. Second, because we predict compensation in the same way that it is calculated for individual soldiers, it is easier to model policy changes. For example, to determine a soldier's basic pay in the future we must predict his or her pay grade by year of service. Given this first step, it is straightforward to assess the effects of changes in promotion policy on military compensation. In a regression model, promotion and longevity effects are usually confounded in a coefficient on years of service.

First, we describe the components of military compensation included in our estimates and outline the data sources and methods used to calculate each component for a soldier at a reenlistment decision point. We next present the models used for predicting a soldier's promotion times to higher grades, a key first step in calculating several of the components of military compensation. Differences in promotion times are the mechanism by

which differences in performance and ability are translated into differences in military compensation. Thus, the relationship between promotion times and soldier characteristics is also interesting in its own right. Because allowances are different for soldiers with and without dependents, we also predict "dependents status." Finally, the methodology is described.

Components of Military Compensation

The components of military compensation are basic pay, allowances for housing and subsistence, reenlistment bonuses, special pays for hazardous or arduous duty, medical care for the member and dependents, paid leave, tax benefits of non-taxable allowances, retirement pay, and educational benefits. This section discusses which elements are included in our estimates of military compensation, who is eligible to receive them, and how their values are estimated.

Basic Pay

As shown in Table C-1, basic pay is the largest component of military compensation. A soldier's basic pay in any year is determined by year of service (YOS) and pay grade, and the basic pay table is typically adjusted on an annual basis. To predict basic pay for a soldier at a reenlistment point, we use the pay table for the year in which the decision is being made.[68] Starting with the soldier's grade and year of service at the decision point, we "age" him or her through the pay table, increasing years of service and adding promotions as predicted from promotion time models.[69]

It is interesting to note how an increase in grade affects basic pay compared to changes in YOS. For an E-4 making a first reenlistment decision at YOS 3 in FY 1983, basic pay will increase by approximately 7.8 percent over the next *two* years, while a step in grade (at YOS 3) increases basic pay by 9.5 percent. An E-6 making a second-term reenlistment decision at YOS 6 can expect a 3.7 percent longevity increase over the next two years and a 13.5 percent promotion increase.

Table C-1
Annual Pay Amounts at First and Second Reenlistment Points[a]

	First Term		Second Term	
Pay Component	**No Dependents**	**With Dependents**	**No Dependents**	**With Dependents**
Basic Pay	$7,869	$7,869	$10,556	$10,556
BAQ	1,632	2,431	1,926	3,010
BAS	1,597	1,597	1,597	1,597
VHA	466	634	708	971
SRB[b]	2,623	2,623	3,519	3,519
Total	$14,187	$15,154	$18,306	$19,653

[a]Individuals shown are at ETS in FY 1983. First- and second-term individuals are E-4 with YOS 3 and E-6 with YOS 6 respectively. Pay amounts are shown in 1980 dollars.

[b]SRB amount is based on SRB multiple of one and reenlistment contract of four years. Lump-sum payment method is applied to show total value of bonus even though this policy was not active in FY 1983.

Allowances

The Basic Allowance for Quarters (BAQ) is paid only to enlisted personnel who are *not* furnished government housing. However, we include the allowance in the military compensation of all soldiers because we cannot assess the value of in-kind benefits. BAQ rates vary by pay grade and dependents status, and are adjusted annually.[70]

Future BAQ amounts are based on expected future pay grade and dependents status. The existing dependents status is assumed to persist for those currently with dependents. For individuals with no dependents, future BAQ amounts are projected as a weighted average of the with- and without-allowance amounts, where the weight is the expected probability of obtaining dependents. (The dependents status model is described later in more detail.)

Enlisted members who do not have access to mess facilities are entitled to receive the Basic Allowance for Subsistence (BAS). It is paid at a daily rate, and is the same for all grades. Rates are updated annually. Our estimate of military compensation includes BAS for all soldiers.

The Variable Housing Allowance (VHA), initiated in FY 1981 to augment BAQ in high-housing-cost regions, is paid to soldiers in CONUS assignments who do not reside in government quarters. VHA rates, updated annually, vary by pay grade and the area of assignment.

Due to frequent PCS moves, a member's current VHA is not necessarily the expected value of this benefit for his or her career. Consequently, we use all-DoD averages, which are published by fiscal year, dependents status and grade, to estimate future benefit amounts.[71] As described in the BAQ section, the With- and Without- Dependents VHA rates are also weighted by the respective probabilities of having or not having any dependents for a given year in the future.

Allowances—BAS, BAQ, and VHA—are not considered taxable income, and hence have an increased value in comparison with pretax civilian income. The tax benefits that accrue from these allowances are omitted from our military compensation estimates. While the amounts may be substantial, the difficulties inherent in estimating tax benefits are also large. We considered using published Department of Defense tax advantage figures, but two problems with the data suggest it would be better to omit the measure entirely rather than introduce inaccuracy. First, the estimates did not account for compensation received by the member's spouse, which would have a large effect on the tax advantage. Second, the tax advantage was proportionately the same at the first and second reenlistment points and, therefore, would not affect the estimated pay elasticity.

Reenlistment Bonuses

The Selective Reenlistment Bonus (SRB) program, in effect through most of the AVF period, was designed to induce individuals to stay in the Army by providing bonuses for reenlistments in certain skill areas. The SRB dollar amount is simply the product of the appropriate SRB multiplier, contract length in years, and monthly basic pay. The multiplier varies with a soldier's MOS (also skill identifier and grade in recent years), YOS at reenlistment (zone A, B, or C), and ETS date. In addition, the method of payment—lump sum, installment, or combined—has changed over time.

SRB multipliers are based on data from the Army Personnel Command. A PERSCOM document lists SRB multipliers by primary MOS, skill identifier, reenlistment zone, pay grade, and effective dates. Based on this, an SRB multiplier data set was constructed, by half-fiscal year period, MOS, skill, zone, and pay grade, containing the largest multiplier level attained during the period. Table C-2 shows average SRB multipliers at the first and second reenlistment points for our analysis sample.

Table C-2
Mean SRB Multipliers[a]

	First Reenlistment Point			Second Reenlistment Point		
Fiscal Year	Infantry	Mechanics	Admin.	Infantry	Mechanics	Admin.
1976	1.913	.827	.211			
1977	1.916	.276	.000			
1978	.959	.486	.000	1.000	.000	.000
1979	.912	.848	.000	.900	.757	.065
1980	.921	.723	.001	.439	.435	.000
1981	1.867	.492	.000	1.784	.532	.005
1982	1.934	.510	.002	1.088	.454	.000
1983	.695	.592	.000	.672	.380	.000
1984	1.639	.701	.000	1.006	.347	.000
1985	.942	.934	.000	.452	.304	.000
1986	.740	.557	.000	.581	.095	.000
1987	.785	.255	.000	.144	.014	.000
All	1.154	.587	.002	.661	.272	.001

[a]Average multipliers in our analysis samples.

The reenlistment contract length assumed in calculating the bonus amount depended on the horizon over which ACOL was computed. A three-year horizon implies a three-year contract; for any horizon greater than three years, we assume a four-year contract. Three major types of SRB payment policies were in force over the analysis period: lump sum, installment, and combined. These policies are modeled by dividing the SRB dollar amount into a number of payments over contract length years as appropriate for the policy in force.

Two other assumptions were made in computing bonuses. First, Army policy generally dictates that bonuses are not paid to soldiers who change their MOS at reenlistment, and in our baseline model we follow this rule.[72] Second, only reenlistment bonuses for the current decision point are included in military earnings estimates. While an individual expecting to stay eight more years may anticipate two SRB bonuses, the second one is ignored in our military compensation estimates. To include bonuses for future reenlistments based on actual multipliers in the future would assume perfect foresight on the soldier's part, an unreasonable assumption given their large variation over time. Applying an average multiplier would simply shift everybody's military compensation up by a similar amount.

Retirement Benefits

Service members are eligible to receive retirement benefits if they separate with 20 or more years of service. Annual retirement pay is calculated as 50 percent of annual basic pay at YOS 20 for soldiers who entered the Army before FY 1980. For the soldiers in our sample who accessed in fiscal years 1980 through 1984, a high-three average (the average of basic pay over the last three years) is used instead of basic pay at YOS 20. Benefits are fully indexed to inflation.

Education Benefits

A variety of different programs have provided educational benefits to individuals who enlisted in the Army during the AVF period. Using accession information from the EPRDB, we assigned each soldier the discounted present value of the (net of contributions) education benefits for which he was eligible, as shown in Table C-3.

The estimated values are entered in the reenlistment models separately rather than being incorporated directly in our measure of military compensation. Education benefits are a "tied" form of compensation because the money can be applied only for a certain good (schooling). This restriction reduces the utility value of these dollars, as compared with other compensation, implying that different coefficients are required.

Table C-3
Educational Benefit Amounts

Benefit Program	Enlistment Term	Kicker Amount	Net Present Benefit Value[a]
GI Bill (1972–1976)[b]			
No dependents	3		$ 9,070
2 dependents	3		12,301
VEAP[c] (1977–1985)	2		1,772
	3		1,981
	4		1,904
Super VEAP[c] (FY80–82)	2	$2,000	2,426
	3	4,000	3,202
	4	6,000	3,509
Non-Contributory VEAP (FY81–82)	2	2,000	4,120
	3	4,000	5,524
	4	6,000	6,345
Tuition Assistance Program (FY81–82)	2		5,313
	3		6,898
	4		7,830
Army College Fund/ Ultra-VEAP (FY81–current)	2	8,000	4,900
	3	12,000	5,931
	4	12,000	5,153

[a]Benefit amounts reported in 1980 dollars. Present value calculations assume a 20% discount rate.

[b]Dates of operation shown in parentheses.

[c]Contributory programs assume maximum contribution, but the contributions are subtracted from the benefits before discounting.

Special Pays and Other Benefits

The special and incentive pays for which a member may be eligible include hazardous duty pay, allowances for family separation, uniforms, and permanent change of station, or proficiency pay for recruiters and drill instructors. For the most part, the values of these special pays are small relative to total compensation for Army enlisted personnel. Since receipt of these pays is not identified on the enlisted master files, data would have to be merged from other sources, such as personnel financial tapes. The benefits gained from including the pay elements probably do not justify the effort required to obtain the data.

The free medical care received by military members and their families is omitted from military compensation estimates. While the value of the benefit may be large, most civilian employers also provide free medical coverage. Hence, no

modeling benefits would arise from adding health-care values to both the military and civilian pay estimates.

Modeling Promotion Times

This section describes how we predict expected promotion times, the number of months it takes to advance from one grade to the next, for a soldier making a reenlistment decision. In the military compensation system, differences in promotion times are the mechanism by which differences in performance and ability are translated into differences in military pay. Because of this role, a small literature examining the link between promotion times and soldier characteristics, such as race and education, has developed. Before presenting our results, we will briefly review two relevant studies.

Butler (1976) uses promotion times to assess racial equality in Army personnel policy. With data for soldiers on active duty in 1973, he compares months in service at promotion to grades E-4 through E-9 across groups defined by race, score on the Armed Forces Qualification Test (AFQT), education, and occupation type (technical/nontechnical).[73] Using cross-tabulations, he finds that blacks take longer to achieve a given grade than whites, holding constant the other characteristics. No hypothesis tests are calculated, but the differences are large, averaging over 30 percent for E-5 and E-6, for example. He also finds that time in service at promotion falls with higher education but rises with AFQT, an unexpected result as both variables are used as accession screens to predict future success in the military. Finally, the differences between soldiers in technical and nontechnical occupations are found to be small.

A methodological weakness of Butler's study is the use of cross-sectional data that includes only those members of an accession cohort who "survive" to the observation point. Ignoring the significant amount of censoring that occurs through attrition and reenlistment decisions—less than 20 percent of the members of a typical infantry cohort make it to the second term—could lead to a finding of racial discrimination in Army promotion policies when, in fact, none exists.

Consider the following example. Suppose that promotions are based only on performance, so that blacks and whites at the same performance level are paid the same in the Army. If blacks face earnings discrimination in the private sector relative to whites, blacks will find the Army a more attractive career than whites at the same performance level because their relative military-civilian earnings are higher. Even though the Army does not discriminate, the average performance level and, therefore, average promotion times of blacks who stay in the Army will be lower than that of whites who stay. If the other characteristics in the promotion model do not fully capture the performance differences between blacks and whites, we will incorrectly conclude that promotion policies are discriminatory.[74]

Daula and Nord (1985), hereafter called D-N, also estimate the relationship between promotion times and soldier characteristics, but from a different perspective. They argue from institutional characteristics that promotion times are, in fact, a valid measure of soldier performance and seek to estimate the link between accession characteristics, such as AFQT, and performance.[75]

Recognizing the potential for censoring bias, D-N use a duration or hazard model to analyze promotion times to E-5 and E-6 for eight Army MOSs. Instead of ignoring individuals for whom promotion times are not observed, a hazard model incorporates the information that they survived to the censoring point into the estimation of the parameters. To estimate their model, D-N construct a sample of soldiers who were E-4's and E-5's in 1980 through 1984. Annual personnel records are used to determine the promotion time, if a soldier was promoted, or the censoring time, if the soldier separated from the Army or was not promoted before the end of the observation period.[76] The distribution of promotion times is assumed to be Weibull, which has a uniformly increasing or decreasing probability density function, depending on the "shape" parameter.

Compared with Butler, D-N have a richer set of explanatory variables in their model. They include years of education (with a dummy variable for a GED), AFQT, race, sex (for occupations with female soldiers), marital status,

number of dependents, time in service at the previous promotion, and dummy variables for the fiscal year of the previous promotion. D-N find that:

- In contrast to Butler's findings, the effect of race on promotion times is generally statistically insignificant. Where it is significant, blacks are promoted faster in one case and slower in two others.
- Soldiers with more years of education and higher AFQT scores are promoted faster. A 30-point increase in AFQT (35 to 65) is associated with promotion times to E-5 that are between 8 percent and 19 percent faster, depending on the occupation. Results are similar for E-6 promotions.
- In most occupations female soldiers have slower promotion times than males, holding constant other factors.
- There is no consistent relationship between marital status/dependents and promotion times.
- Soldiers with longer time in service at their previous promotion are promoted *faster* to the next grade.

The last result is, at first, surprising if promotions are based on performance. One would expect a positive correlation between time in service, the sum of previous promotion times, and the current promotion time. However, as the authors note, minimum time-in-service requirements for promotions slow down promotion times for those promoted more quickly to the previous grade, inducing the negative correlation observed.[77]

The rest of this section is organized as follows. First, we outline the methodology and data used to estimate the promotion time models in this analysis. Then, we present the estimation results and describe how promotion time predictions are generated from the estimated models.

Methodology and Data

For promotions to grades E-4, E-5, and E-6, our approach follows D-N, with some minor differences in the estimation

procedure and data used. For the remaining grades E-7 to E-9, data limitations force us to estimate promotion times from cross-sectional data, as Butler does. We describe each approach and the data used in turn.

Promotions to E-4 through E-6. Let $t_{i,g}$, the time from grade g-1 to g for the ith individual, be given by

$$\ln(t_{i,g}) = X_i\beta_g + \varepsilon_i \tag{C.1}$$

where X_i is a vector of the soldier's characteristics, such as AFQT and race, and β_g is a vector of parameters to be estimated. We assume that the error term, ε_i, has a normal distribution with zero mean and variance σ^2, so that promotion times are distributed log-normal.

Figure C-1 shows the distribution of observed promotion times to E-5 for a sample of soldiers in the Infantry, Mechanical Maintenance, and Administration CMFs who enlisted between 1974 and 1984.[78] This figure illustrates two points. First, note that the log-normal distribution provides a reasonable characterization of the distribution of promotion times, which results from certain institutional features of Army promotion policy. Minimum time-in-grade requirements cause promotions to concentrate around certain "zones." These requirements, however, can be waived for a limited number of personnel, giving the distribution a skewed shape. Second, there seem to be

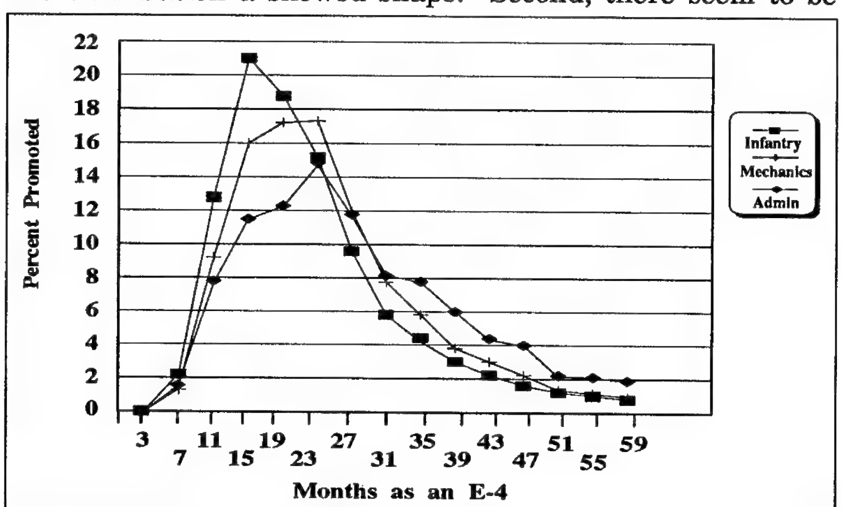

Figure C-1. E-5 Promotion Times

significant differences across the CMFs in promotion times. For this reason, we will estimate separate models by CMF.

As noted above, t will not be observed for all soldiers because of attrition and separation at ETS. Individuals with censored promotion times can be incorporated into the estimation of the model because we know that their promotion time must be greater than their time-in-grade at the point they leave. In particular, the log-likelihood function for this model is

$$\text{(C.2)} \qquad \ln L = \sum_i \left[(1-c_i)\ln\{\phi(A)/\sigma\} + c_i \ln\Phi(-A)\right]$$

Where $A = (\ln t_{i,g} - X_i\beta_g)/\sigma$;

$\phi()$, $\Phi()$ are the standard normal density and cumulative probability functions; and

$c_i = 1$ if the observation is censored, and 0 otherwise.

In this formulation, t is either the promotion time or censoring time, depending on the status of the observation.[79]

Two assumptions about the censoring of promotion times should be noted. First, in addition to separation before promotion, censoring also occurs because the observation period ends before promotion or because of demotion to a lower grade. Because the censoring associated with demotions may not be exogenous, we estimated models with and without these individuals but found no significant differences in the parameter estimates.[80]

Second, this model, like that used by D-N, only accounts for the censoring that occurs between promotions. To obtain unbiased predictions of future promotions for an E-4 at the first reenlistment point, we should estimate a joint model of E-5 and E-6 promotion times, allowing for a correlation between the ε's associated with each grade. This model would recognize that individuals censored before promotion to E-5 are not in the sample for the E-6 promotion model, raising the possibility of sample selection bias. Because of the problems in identifying this model and the limited effect further refinements in promotion models would have on our predictions of military earnings (see below), we simply estimate separate models for promotion to E-4, E-5, and E-6.

The data sets used to estimate the promotion time models are derived from the Enlisted Panel Research Data Base (EPRDB), a longitudinal file of AVF accessions, which is described in Appendix B. Soldiers in each CMF were identified when promoted to grades 3, 4, and 5 and tracked until promoted to the next highest grade or censored. Individual characteristics are measured at the time of promotion to the source grade; individuals with missing data were excluded from the estimation samples.

Promotions to E-7 through E-9. Sufficient longitudinal data are not available to estimate hazard models of promotion times to E-7 and above for soldiers who enlisted during the AVF period. Typically, a soldier is promoted to E-7 with 11 to 13 years of service, so that only the earliest AVF accession cohorts could be used to model even E-7 promotion times.

Instead, we calculate mean promotion times, by CMF, for each grade using recent cross-sectional data. The mean time in service at last promotion for soldiers on active duty at the end of FY 1986 is computed, by CMF, for grades 6 through 9 using the DMDC enlisted master files. Promotion times are just the difference between these values for successive grades. As we will show below, these means understate the expected promotion times for all soldiers because, like Butler's analysis, they ignore the censored observations.

This approach also eliminates any individual-specific variation in promotion times at the senior grades. While less attractive in principle than using promotion time models, the simple means accurately reflect our ability to predict differences in promotion times for these grades. We estimated time in service models for grades 6 through 9 using the 1986 data and found few significant relationships between promotion times and the individual characteristics used in the promotion time models for the junior grades.[81]

Estimation Results and Promotion Time Predictions. Table C-4 displays mean values for the variables in the promotion time models. Tables C-5 through C-7 show the parameter estimates for the log-normal hazard models of promotion times to grades 4, 5, and 6.

The mean promotion times predicted from the models are shown at the bottom of the tables with the parameter estimates. These predicted means for all soldiers in the source grade are significantly longer than the mean promotion times observed for soldiers who remain in the Army through their promotion point. For example, the observed mean for infantry promotions to E-5 is 21 months while the mean generated from the hazard model is 37 months. For E-6 promotions, the observed and generated means are 33 and 54 months, respectively. These results imply that soldiers who leave have longer expected promotion times, which is reasonable given that longer times imply lower military pay and, probably, lower performance. These results also imply that predictions of military pay based on cross-sectional data, either directly through military compensation regressions or indirectly through promotion time models, will overstate the expected value of a soldier's future military compensation.

Given the similarities in methods and data, it is not surprising that our results generally confirm the findings of Daula and Nord. In particular, we find that

- In only one instance, infantry promotions to E-6, is there any evidence that minority soldiers have longer promotion times than nonminority soldiers, controlling for the other factors in the models.
- More years of education and higher AFQT scores are associated with faster promotions. For each additional year of schooling, promotion times fall between 4 percent and 8 percent, depending on the occupation group and grade.[82] AFQT effects are largest for E-5 promotions, where a soldier with an AFQT score of 65 is predicted to have promotion times 13 percent to 18 percent faster than a soldier with an AFQT of 35.
- We find a less pervasive pattern of slower promotion times for women than D-N. In the Administration CMF, which has the greatest proportion of female soldiers, the only significant gender difference in promoting times is to E-5. As the presence of women in the enlisted ranks has grown over time, the difference in results may be due to the fact that our sample includes more recent observations on promotion experience.

Table C-4
Promotion Models Means[a]

Variable	Promotion E3–E4 INF	Promotion E3–E4 MECH	Promotion E3–E4 ADMIN	Promotion E4–E5 INF	Promotion E4–E5 MECH	Promotion E4–E5 ADMIN	Promotion E5–E6 INF	Promotion E5–E6 MECH	Promotion E5–E6 ADMIN
Minority	0.340	0.277	0.566	0.340	0.286	0.558	0.332	0.324	0.567
Female	—	0.050	0.413	—	0.046	0.405	—	0.047	0.366
Married	0.183	0.223	0.227	0.286	0.330	0.357	0.514	0.612	0.598
Number of Dependents	0.336	0.377	0.329	0.520	0.559	0.503	1.015	1.205	1.027
Years of Education	11.714	11.641	12.270	11.827	11.744	12.360	12.100	12.005	12.734
AFQT	45.350	40.813	48.306	46.319	41.368	49.844	51.105	42.886	52.666
Prior Service	0.060	0.035	0.041	0.091	0.060	0.071	0.169	0.140	0.150
Accession FY 77–79	0.289	0.340	0.332	0.289	0.331	0.322	0.330	0.385	0.413
Accession FY 80–82	0.365	0.310	0.354	0.330	0.288	0.317	0.337	0.279	0.280
Accession FY 83–84	0.221	0.245	0.193	0.236	0.256	0.207	0.178	0.194	0.096
Months to Current Grade	11.525	11.824	0.699	21.925	21.261	19.859	42.117	44.197	44.710

[a]Samples are based on data from the EPRDB and contain soldiers in pay grades 3, 4, or 5 who are tracked until promoted or censored.

Table C-5
E-4 Promotion Models[a]

	Career Management Field		
	Infantry	Mechanics	Administration
Intercept	3.231	2.911	3.039
	(0.070)	(0.055)	(0.057)
Minority	–0.006	–0.003	0.018
	(0.014)	(0.010)	(0.013)
Female		0.011	–0.012
		(0.021)	(0.115)
Married	–0.058	0.007	–0.004
	(0.026)	(0.015)	(0.018)
Number of Dependents	0.006	–0.018	0.004
	(0.013)	(0.007)	(0.009)
Years of Education	–0.050	–0.040	–0.056
	(0.006)	(0.005)	(0.005)
AFQT	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Prior Service	0.019	–0.033	0.001
	(0.026)	(0.023)	(0.025)
Accession FY 77–79	–0.064	–0.045	–0.015
	(0.021)	(0.015)	(0.019)
Accession FY 80–82	0.041	0.055	0.119
	(0.021)	(0.015)	(0.019)
Accession FY 83–84	–0.032	–0.033	–0.088
	(0.023)	(0.016)	(0.020)
Months to E-3	–0.010	–0.001	–0.003
	(0.001)	(0.000)	(0.000)
σ	0.561	0.559	0.541
	(0.005)	(0.003)	(0.004)
Mean Promotion Times	14.094	13.024	12.293
Number of Observations	9,495	19,690	11,148

[a]Log-normal hazard models of months to E-4 promotion estimated with AVF accessions. Standard errors are in parentheses.

Table C-6
E-5 Promotion Models[a]

	Career Management Field		
	Infantry	**Mechanics**	**Administration**
Intercept	4.320	4.791	4.645
	(0.112)	(0.086)	(0.093)
Minority	0.028	–0.010	–0.009
	(0.020)	(0.014)	(0.018)
Female	—	0.017	0.085
		(0.028)	(0.016)
Married	–0.073	–0.068	–0.025
	(0.028)	(0.018)	(0.020)
Number of Dependents	0.010	–0.044	–0.037
	(0.013)	(0.009)	(0.011)
Years of Education	–0.047	–0.083	–0.065
	(0.010)	(0.007)	(0.007)
AFQT	–0.006	–0.004	–0.006
	(0.000)	(0.000)	(0.000)
Prior Service	–0.116	–0.152	–0.225
	(0.027)	(0.021)	(0.027)
Accession FY 77–79	–0.112	–0.026	–0.002
	(0.027)	(0.020)	(0.024)
Accession FY 80–82	–0.085	0.098	0.224
	(0.026)	(0.021)	(0.025)
Accession FY 83–84	0.049	0.100	0.338
	(0.030)	(0.021)	(0.029)
Months to E-4	–0.001	–0.002	–0.000
	(0.000)	(0.000)	(0.000)
σ	0.636	0.621	0.639
	(0.008)	(0.005)	(0.007)
Mean Promotion Times	37.114	43.510	48.521
Number of Observations	9,647	21,326	12,659

[a]Log-normal hazard models of months to E-5 promotion estimated with AVF accessions. Standard errors are in parentheses.

Table C-7
E-6 Promotion Models[a]

	Career Management Field		
	Infantry	**Mechanics**	**Administration**
Intercept	4.943	5.1919	5.603
	(0.181)	(0.170)	(0.137)
Minority	0.138	0.034	−0.006
	(0.033)	(0.024)	(0.031)
Female	—	0.168	0.046
		(0.067)	(0.031)
Married	−0.069	−0.016	−0.113
	(0.041)	(0.029)	(0.031)
Number of Dependents	−0.002	−0.009	0.012
	(0.015)	(0.011)	(0.013)
Years of Education	−0.074	−0.062	−0.074
	(0.015)	(0.014)	(0.010)
AFQT	−0.002	−0.003	−0.004
	(0.001)	(0.001)	(0.001)
Prior Service	−0.292	−0.159	−0.195
	(0.034)	(0.027)	(0.035)
Accession FY 77–79	−0.011	−0.076	−0.042
	(0.040)	(0.030)	(0.034)
Accession FY 80–82	−0.049	−0.150	−0.147
	(0.040)	(0.032)	(0.037)
Accession FY 83–84	−0.009	−0.222	−0.288
	(0.069)	(0.047)	(0.078)
Months to E-5	−0.001	−0.003	−0.004
	(0.000)	(0.000)	(0.000)
σ	0.5666	0.524	0.573
	(0.012)	(0.009)	(0.011)
Mean Promotion Times	54.544	63.371	74.218
Number of Observations	3,716	7,094	4,655

[a]Log-normal hazard models of months to E-6 promotion estimated with AVF accessions. Standard errors are in parentheses.

- Married soldiers and those with dependents generally have shorter promotion times, although the differences are small.
- Like D-N, we find that soldiers with a history of faster promotions, as measured by time in service at promotion to the source grade, take *longer* to be promoted to the next grade. In results not reported here, we measured promotion time relative to the minimum time that each soldier had to serve in a grade given his or her time-in-grade and time-in-service requirements. With this dependent variable, we found that faster previous promotions implied faster current promotions after the minimum requirement was satisfied. This is the relationship that would be expected if promotion times were indicative of individual performance.
- Prior-service soldiers have faster promotion times to grades E-5 and E-6. There are two related explanations for this result. First, prior-service soldiers typically return to the Army at a lower grade than their grade at separation and, therefore, have already demonstrated the skills required for that grade. Second, given the financial cost associated with an interrupted military career, it is likely that prior-service soldiers may be more motivated than the average soldier.
- The fiscal year of accession variables are included to measure any differences in promotion times due to macro factors, such as changes in the manpower requirements at each grade, deceleration of promotions in response to budget pressures, or differences in accession cohort size. Promotion times to E-4 were relatively stable over the analysis period. In contrast, average promotion times increased significantly for E-5 promotions and declined for E-6's.

To assess the variation in military compensation associated with differences in promotion times, we predict military compensation (the prediction equations are described below) between YOS 4 and YOS 12 for two soldiers in the Infantry CMF who differ only in their AFQT score—one with

65, the other with 35.[83] Assuming a 10 percent discount rate, the annualized military compensation for the high-AFQT soldier is just 1.1% higher than that of the low-AFQT soldier.

There are two reasons for the small difference. First, because of the structure of the basic pay table, any pay difference attained through faster promotion lasts only until the low-AFQT individual is promoted. With the same years of service and grade, soldiers are paid the same. Second, as we have noted, the advantage of fast promotion to one grade is partially negated by slower promotion to the following grade because of time-in-service minimums. Given the AFQT difference alone, we would predict that the high-AFQT soldier would be promoted 13% faster to E-6. However, because of the minimum time-in-service requirement, we estimate that the difference is just 5%.

The estimated models are used to predict promotion times to E-4 through E-6 as follows. If the soldier is currently in grade g, the time to promotion to grade g+1 is predicted conditional on existing time in grade g at ETS, which we denote as t_0. The formula is

$$\text{(C.3)} \qquad E\,(t_{g+1} \mid t_{g+1} > t_0) = \exp(\sigma^2/2 + X_i\,\hat{\beta}_{g+1})\,[\Phi(\sigma - A_0)\ /\ \Phi\,(-A_0)]$$

$$\text{where } A_0 = (\ln t_0 - X_i\,\hat{\beta}_{g+1})\,/\sigma$$

This predicted time, along with the other individual characteristics, is then used to predict the unconditional time to grade g+2, given by

$$\text{(C.4)} \qquad E\,(t_{g+2}) = \exp(\sigma^2/\,2 + X_i\,\hat{\beta}_{g+2})$$

This procedure is repeated through grade 6.

Table C-8 displays the mean promotion times from the next lower grade to grades 7, 8, and 9 calculated from the 1986 cross-sectional data.

Table C-8
Mean Promotion Times to E-7, E-8, and E-9[a]

Career Management Field	E-7	E-8	E-9
Infantry	54	59	68
Mechanical Maintenance	53	63	66
Administration	50	56	64

[a]Promotion times are measured in months.

Predicting Dependents Status

For soldiers who do not have dependents at the reenlistment decision point, we assign future housing allowances that are a weighted average of the allowances for soldiers with and without dependents. Assume that a soldier without dependents is making a reenlistment decision in year t. The allowance assigned to him or her in some future year t+j is

$$A_{t+j} = A^{d}(1 - p_{t+j}) + A^{nd}\, p_{t+j} \tag{C.5}$$

where A^d and A^{nd} are the allowances (at their pay grade) for soldiers with and without dependents, and p_{t+j} is the probability that he or she still has no dependents in year t+j.

As soldiers with dependents are more likely to reenlist than those without, p's estimated from cross-sectional data would overstate the probability that the average soldier without dependents at a given reenlistment point would have some at a future year of service. Thus, allowances for these individuals would be too high. Instead, we use a simple hazard model, a lifetable, to calculate the p's. Let d_{t+1} be the conditional probability that a soldier with no dependents in year t has at least one dependent in year t+1. Then,

$$p_{t+j} = \prod_{n=t+1}^{t+j} (1 - d_n) \tag{C.6}$$

the probability of not having dependents in year t+j is just the product of the conditional probabilities of not acquiring dependents in years t+1, t+2, and so on. The d's are calculated separately for each CMF using soldiers in the EPRDB who accessed without dependents. Table C-9 displays these conditional probabilities.

As an example of how these values are applied, consider an infantry soldier at YOS 4 with no dependents. The probability that he will acquire at least one dependent by the end of his next term (end of YOS 8) is 47 percent. There is a 53 percent probability that he will have at least one dependent by the end of two terms (end of YOS 12).

Table C-9
Conditional Probabilities of Acquiring Dependents[a]

	Career Management Field		
YOS	**Infantry**	**Mechanics**	**Administration**
1	0.1501	0.1747	0.1625
2	0.1106	0.1196	0.1277
3	0.1240	0.1301	0.1483
4	0.1724	0.1608	0.1581
5	0.1915	0.1887	0.1758
6	0.1514	0.1525	0.1534
7	0.1279	0.1226	0.1305
8	0.1051	0.0997	0.1213
9	0.0576	0.0646	0.0573
10	0.0358	0.0230	0.0576
11	0.0080	0.0149	0.0337
12	0.0083	0.0044	0.0102
13	0.0000	0.0023	0.0071
14	0.0000	0.0000	0.0000

[a]Assumes member has no dependents at accession. Based on FY 1986 sample of non-prior service enlisted members.

Appendix D: Post-service Earnings Predictions

This appendix describes how we generate the post-service earnings predictions used in our ACOL variable. Because the variation in military compensation among soldiers at a given year of service is limited, differences in post-service earnings play an important empirical role in determining the relationship between relative pay and reenlistment.

First, we briefly review the literature on post-service earnings models, focusing on the studies most relevant to our analysis. We then describe the data set we use, the Post-Service Earnings History File created by the Defense Manpower Data Center (DMDC). Next, we discuss model specification issues, and present the estimation results. Finally, we describe the prediction methodology.

Literature Review

Every structural model of military retention requires predictions of post-service earnings, and a variety of different models and data sets have been used to generate these predictions. Rather than categorize all these approaches, we focus on the two studies most closely related to our analysis.[84]

Goldberg and Warner (1984,1987), hereafter called G-W, estimate post-service earnings models with data on veterans who served as enlisted personnel and left the Army, Air Force, Navy, and Marines in FY 1971. For confidentiality reasons, the population of separatees was grouped into cells defined by branch, two-digit DoD occupation code, and year of service (YOS) at separation, and sampled to obtain a maximum of 40 observations in each cell. Summary statistics on the annual earnings of veterans in each cell from 1972 through 1977 were provided by the Social Security Administration (SSA).

G-W estimate separate log-linear models by occupation group. In constructing the dependent variable, they delete zero earners because they want to focus on the "permanent" earnings potential of veterans, not transitory disturbances due to schooling or unemployment, and adjust the cell means for the

SSA reporting limit.[85] They assume that post-service earnings are a function of

- Quadratic expressions in military work experience, measured by YOS, and civilian work experience, measured by years since separation.
- An interaction between military and civilian experience, so that years of service can affect the slope as well as the intercept of the earnings-civilian experience profile.
- Percent white and average years of education for each cell.
- The average retirement annuity for veterans in each cell. Because of their focus on full-time earnings, they include the annuity to adjust for the income effect of military retirement benefits on labor supply behavior.
- Service branch dummy variables.

G-W find a 6 percent to 11 percent percent return to an additional year of civilian work experience, depending on the occupation group.[86] The post-service earnings increase due to military work experience is generally lower. This is reasonable given that all veterans are job-changers; and most studies of civilian employment find that, year-for-year, tenure on the current job has a greater effect on earnings than previous experience. An additional factor reducing the average return to military experience is that most veterans do not work in civilian occupations related to their military job.[87]

There is also evidence in G-W's results that the difference between the returns to military and civilian work experience is related to the extent with which military training can, at least potentially, be transfered to the civilian labor market. The difference was largest for the combat occupations, where there is no analogous civilian employment, and smallest for electronics repair, mechanical maintenance, and other technical occupations.

Besides the experience effects, G-W find that earnings increase with a veteran's years of education and, controlling for other factors, are higher for whites. They also find that earn-

ings are negatively related to the size of a veteran's retirement annuity.

The analysis by Daula (1981) differs from G-W in several important aspects. He uses the Vet-Merge File, which contains *individual* observations on five post-service years of earnings for veterans who left military service in FY 1969. Because of the requirements of the reenlistment analysis for which his earnings models are estimated, Daula's results are more narrowly focused than G-W. He estimates models only for Army veterans who served in combat occupations and who left after their first term of service.

Daula specifies a log-linear model with a richer set of military career and personal characteristics as explanatory variables. In addition to work experience variables (years of total experience and years of military experience), education and race, he includes the veteran's score on the Armed Forces Qualification Test (AFQT), pay grade at separation, and a dummy variable indicating if the veteran was drafted.

This earnings model is estimated both by ordinary least squares (OLS) and jointly with the reenlistment model. The latter approach allows Daula to test for sample selection bias in the OLS estimates, a potential problem when the model is to be used to predict post-service earnings in a reenlistment analysis. The relative pay variable in a reenlistment model must be constructed for *all* soldiers at a reenlistment point, but we can only observe post-service earnings for those who leave. If the separatees have better civilian earnings opportunities than those who reenlist and the differences are not captured by the explanatory variables in the earnings model, OLS estimates of the earnings model will provide biased predictions for the whole population of soldiers making a reenlistment decision. In particular, we will overestimate the coefficients on variables in the earnings model that are also positively related to the probability of reenlistment and underestimate the coefficients on variables with a negative correlation.[88]

Daula's OLS results are qualitatively similar to those found by G-W, but there are differences in the magnitude of the coefficients that may be due to the differences in data and focus between the two studies. For example, Daula finds that total

work experience has a positive effect on post-service earnings and that the return to military work experience is smaller than the return to civilian experience. The experience effects, however, are considerably smaller than those estimated by G-W. He also finds that education is positively related to earnings, and black veterans have lower earnings than whites, other things equal.

The variables unique to Daula's study also have plausible coefficients. Higher AFQT scores, a measure of verbal and mathematical aptitude, are associated with higher earnings. Holding constant military experience, soldiers who leave at a higher pay grade have higher post-service earnings, although this result is not significantly different from zero. This result is intriguing; it suggests that civilian employers value the same qualities that are rewarded in the Army's enlisted promotion system.

When the earnings model is estimated jointly with a reenlistment equation, however, Daula finds evidence of significant sample selection bias in the OLS estimates. The direction of the bias is as hypothesized. For example, the coefficients on race and pay grade, which are positively related to reenlistment, drop substantially from the OLS estimates. However, the point estimates of many of the coefficients in the joint model are substantially different from what would be expected given the general literature on earnings models. For example, the return to an additional year of education is 20 percent, and blacks are found to have over 80 percent lower earnings than whites. Given that OLS estimates with the same data yield reasonable results, one suspects that the estimates from the joint model may be sensitive to the exclusionary restrictions used to identify the model.[89]

G-W also recognize the potential for sample selection bias in their analysis. However, because they use grouped data and because they model the earnings of veterans who leave at different points in their military career, estimation accounting for sample selection is considerably more complicated than in Daula's study. G-W try an *ad hoc* procedure and find no difference in the estimated models, but this could be the result of a weak test. Given the data problems in both studies, the

evidence for or against sample selection bias in OLS estimates of post-service earnings is inconclusive.

DMDC Post-service Earnings History File

Our earnings models are estimated with the Post-Service Earnings History File or PSEHF. The PSEHF contains post-service earnings data for officers and enlisted personnel who separated from the Army, Air Force, Navy, and Marines during the 1970s.[90]

As the peculiar structure of PSEHF places limitations on the analysis of post-service earnings, it is worth detailing its construction.[91] All separations from 1972 through 1980 were screened to eliminate individuals who separated for medical reasons, death, undesirable behavior or performance, or entry into another service. The remaining separations, approximately 2.3 million enlisted personnel and 255,000 officers were placed in cells defined by branch, years of service, education/military pay grade, year of separation, and military occupation category.

Cells with less than three members were discarded. For cells with a population greater than 25, a random sample of 25 members was drawn. Other individual characteristics not included in the definition of a cell, such as AFQT and number of dependents, were averaged within each cell, and the *cell averages* appended to the Social Security numbers of cell members. The resulting file was sent to the SSA, which added the member's reported W-2 earnings—up to the reporting ceiling—for 1972 through 1980 and removed the Social Security numbers. A similar file went to the Internal Revenue Service (IRS) which appended W-2 earnings, up to a confidentiality ceiling of $150,000, for 1979 through 1983.[92]

The PSEHF, then, is a hybrid file. It contains individual data on earnings and on those characteristics that define the cells. Many other characteristics, however, are only available as cell averages. The advantages of the PSEHF for this analysis are its relative timeliness (the data sets used by G-W and Daula did not include any individuals who enlisted during the AVF period), the availability of post-service earnings for up to 12 years after separation, and the good selection of potential explanatory variables.

There are two disadvantages. First, there is no labor supply information on the file. Military earnings in our analysis are measured on a full-time basis. To correctly characterize the financial consequences of the choice between military and civilian occupations, we should also measure post-service earnings on a full-time basis. Our models of post-service earnings include variables to adjust for the difference between actual and full-time earnings, such as the unemployment rate; but this is second best to actually observing full-time earnings.

Second, the structure of the PSEHF dictates that we estimate earnings models with grouped data. As many of the explanatory variables are cell averages, earnings models estimated with the individual records of the PSEHF would suffer from a potentially severe errors-in-variables problem.[93] Grouping the data, however, complicates the task of testing and adjusting for potential sample selection bias. For example, variation in military pay is the major factor identifying a sample selection model, but grouping occupations eliminates the variation in pay caused by differences in bonuses. An *ad hoc* procedure could be developed using additional data from military personnel files to predict separation probabilities; but, given the experience of Goldberg and Warner, we didn't believe the potential results would be reliable enough to warrant the additional effort.[94]

We use the IRS data in our analysis for three reasons. First, in contrast to the SSA data, no adjustment for the reporting limit is required because only 1 percent of the earnings observations for enlisted personnel are at the limit. Second, the IRS earnings data are more inclusive because of employment that is not covered by the Social Security system.[95] Third, the calendar years covered by the IRS data provide a longer period over which to estimate the effect of civilian work experience.

Model Specification

Following the literature, we estimate a log-linear model,

$$\ln E_{it} = \alpha_0 + \alpha_1 M_i + \alpha_2 M_i^2 + \alpha_3 C_{it} + \alpha_4 C_{it}^2 + \alpha_5 (M_i C_{it}) + X_i \beta + \varepsilon_{it} \tag{D.1}$$

where E is the average of *nonzero* earnings for cell i in year t, deflated to 1980 dollars using the GNP deflator. We exclude observations with zero earnings from the cell averages because our goal is to predict full-time earnings. M is military experience, C is civilian experience, and the X's are other correlates of earnings that will be described below.

Our specification of work experience effects is the same as that proposed by G-W, separate quadratics in military and civilian experience and an interaction term. However, they had to constrain some of the experience parameters because there were only six post-service years of earnings in their data. This is not a problem with the longer horizon available in the PSEHF.

The military retirement system has significant effects both on the pattern of separation rates by year of service and on the potential labor supply behavior of retirees. Both factors could bias the estimated effect of military experience. Given the generosity of the military retirement system, the opportunity cost of leaving rises rapidly approaching the vesting point at 20 years of service; and separation rates show a concomitant drop. Individuals who leave between 12 and 19 years of service, therefore, often are "special" cases, such as disability retirements or disciplinary problems, and are likely to have lower post-service earnings. As noted by G-W, the retirement system may also reduce the labor supply behavior of retirees through an income effect. To isolate both of these effects, we include two YOS index variables, one defined for YOS 13 through 19 and the other for YOS 20 through 30. We expect both variables to have negative coefficients.[96]

Unemployment is another reason that the earnings observed may differ from full-time earnings. Soldiers may experience transitional unemployment as they reenter the private sector, reducing observed earnings in the initial post-service years, and, therefore, overstating the effect of civilian experience on full-time earnings. As a way to adjust for transitional unemployment, we include a "first year out" dummy variable in the model.

Because the earnings observations cover five calendar years with very different unemployment rates, cyclical un-

employment may also be a factor. For this reason, we include the national unemployment rate for all individuals 16 years and older in the model.

Besides work experience, human capital theory suggests that education and performance on previous jobs are potential determinants of earnings. To measure the former, we include the cell-average years of education at separation and Armed Forces Qualification Test (AFQT) score. For the latter, we follow Daula in using pay grade as a performance measure. However, rather than entering pay grade directly, we calculate a *relative* pay grade variable. It is the difference between the average grade for a particular cell and the average grade for all cells in the same accession cohort with the same years of service at separation. Pay grade is highly correlated with military experience. This specification isolates individual performance differences from the general increase in performance one would expect with more experience.

Finally, we include dummy variables for black and female veterans.

We estimate separate earnings equations for the three occupation groups in the PSEHF that include the Infantry, Mechanical Maintenance, and Administration CMFs. The combat group includes veterans who served in armor and combat engineering occupations as well as infantry. For soldiers in mechanical maintenance, we use an occupation group that includes electrical/mechanical repairmen and craftsmen; we will refer to it as the mechanics group. The post-service earnings model for the Administration CMF is estimated with soldiers who served in administration and supply occupations; we will call it the administration group.

The log-earnings models reported below are estimated by OLS. However, there are two distinct reasons to consider the use of weighted least squares (WLS). First, because of the sampling and grouping process used to create the PSEHF, the analysis sample is effectively a stratified sample with different sampling rates by stratum. Although we include as explanatory variables all the characteristics used to define the groups, there may be interaction effects that would lead to biased OLS estimates for this data. To explore this possibility,

we weighted the data as suggested by Hausman and Wise (1981). The results from the WLS estimation were qualitatively the same as those reported below.

Second, models estimated with grouped data, where the group sizes differ, will have heteroskedastic errors. We did not correct for this problem, which affects the efficiency of our estimates, because of the relatively small range of cell sizes and because our primary interest is in using the point estimates for prediction.

Model Estimation Results

Table D-1 displays descriptive statistics for the analysis sample. In general, veterans from the three occupation groups have similiar characteristics. The average number of civilian years of experience is approximately six; the average number of years of military experience is 15. Military experience is higher than one would expect in a random sample of separatees because of the grouped nature of the data. The average post-service earnings, expressed in 1980 dollars, are highest for the mechanics group, although the differences across occupation groups are not large. Similarly, the differences in military career and personal characteristics are small. Average AFQT is marginally higher for the mechanics and administration groups, and the administration group has the largest concentration of female soldiers.

Parameter estimates and standard errors for the post-service earnings models are shown in Table D-2. All the coefficients on the experience variables have the expected sign and are statistically significant. We find a similar return to civilian experience across occupations—about 8 percent per year during the initial years after separation, falling to a zero return at about 20 years of experience for the infantry and mechanics and 29 years for clerks.[97] The returns to civilian experience are moderately smaller for soldiers who leave after a longer military career. Other things equal, a soldier leaving after 20 years of service, for example, is estimated to have annual returns to civilian work experience that are two percentage points lower than a soldier leaving after the first term.

Table D-1
Sample Means

Variable	Occupation Group[a] Combat	Mechanics/ Craftsmen	Administration/Supply
Civilian Experience (yrs)	5.635	5.545	5.650
Military Experience (yrs)	14.921	14.710	15.524
Civilian Experience^2	38.933	38.053	39.149
Military Experience^2	286.291	282.023	306.188
Civilian Exp. × Military Exp.	85.911	83.338	89.837
AFQT	43.993	45.649	47.641
Years of Education	11.501	11.454	11.562
Relative Pay Grade	0.000	0.000	0.000
Black	0.453	0.424	0.424
Female	0.009	0.024	0.102
Unemployment Rate	8.070	8.076	8.070
First Year Out	0.066	0.072	0.066
YOS 13–19 Index	0.467	0.412	0.492
YOS 20+ Index	1.248	1.234	1.454
Annual Earnings (1980 $)	11,395.80	11,813.52	11,350.31

[a]Sample includes observations in the PSEHF on Army enlisted personnel who separated from 1972 through 1980. Earnings are from IRS data for 1979 through 1983.

The returns to military experience are smaller across the board than the returns to civilian experience, ranging from 3 percent to 5 percent per year of additional service. The gap between the returns to military and civilian experience may actually be smaller than we have estimated. G-W argue that their estimated returns to civilian experience are biased upward because of real wage growth over the period they observed post-service earnings. The same critique applies to our analysis where real wages grew at an annual rate of 0.6 percent between 1979 and 1983. G-W also argue that their estimated returns to military experience are understated because of cohort effects, which they estimate from external sources to be

Table D-2
Post-Service Earnings Models[a]

	Occupation Group		
Variable	Combat	Mechanics/ Craftsmen	Administration/Supply
Intercept	8.577	8.405	8.436
	(0.076)[b]	(0.072)	(0.066)
Civilian Experience	0.079	0.079	0.076
	(0.011)	(0.010)	(0.010)
Military Experience	0.029	0.043	0.054
	(0.005)	(0.005)	(0.005)
Civilian Experience^2	–0.002	–0.002	–0.001
	(0.001)	(0.001)	(0.001)
Military Experience^2	–0.001	–0.001	–0.002
	(0.000)[c]	(0.000)	(0.000)
Civilian Exp. × Military Exp.	–0.001	–0.002	–0.002
	(0.000)	(0.000)	(0.000)
AFQT	0.001	0.002	0.000
	(0.001)	(0.001)	(0.000)
Years of Education	0.035	0.044	0.040
	(0.006)	(0.005)	(0.004)
Relative Pay Grade	0.143	0.161	0.137
	(0.009)	(0.009)	(0.007)
Black	–0.006	–0.006	–0.019
	(0.013)	(0.013)	(0.011)
Female	–0.579	–0.449	–0.395
	(0.059)	(0.034)	(0.016)
Unemployment Rate	–0.023	–0.021	–0.010
	(0.004)	(0.004)	(0.003)
First Year Out	–0.079	–0.085	–0.062
	(0.029)	(0.026)	(0.025)
YOS 13–19 Index	–0.014	–0.031	–0.013
	(0.004)	(0.004)	(0.004)
YOS 20+ Index	0.009	0.026	0.040
	(0.007)	(0.006)	(0.006)
Dependent Variable Mean	9.341	9.377	9.337
Mean Square Error	0.260	0.236	0.261
R^2	0.320	0.398	0.357
Number of Observations	2,531	2,450	3,397

[a]OLS estimates of log-normal earnings model (D.1).
[b]Standard errors are in parentheses.
[c]Less than 0.0005 in absolute value.

approximately 0.6 percent. Cohort effects will be smaller in our analysis because we observe separations over a nine-year period rather than G-W's single year. Combining both effects, the gap may be about 1 percentage point smaller than we estimate.

We also find that the returns to military experience vary across occupations in a reasonable fashion. An additional year of military experience as a mechanic or clerk—the occupations with the greatest potential for transferring skills to civilian jobs—has a larger effect on post-service earnings than experience as an infantryman.

Most of the coefficients on the variables included to adjust for the difference between observed and full-time earnings have the expected signs. Observed earnings are negatively related to the national unemployment rate; a 1-point increase in the rate is associated with a 1 percent to 2 percent drop in earnings. There is also evidence of transitional unemployment as separatees' earnings are 6 percent to 8 percent lower in their first year in the civilian market than otherwise would be expected.[98] As we argued, soldiers who leave between 13 and 19 years of service have lower earnings, with the gap increasing the closer the separation point is to potential retirement. The only unexpected finding is for the earnings of military retirees, where we hypothesized that retirement income would reduce labor supply and, therefore, observed earnings. However, for both mechanics and clerks, we find higher than expected earnings for soldiers separating with 20 or more years of service.[99]

Our education and performance measures are significantly related to post-service earnings for most occupations. An additional year of education is associated with approximately 4 percent higher earnings in all three occupations. Soldiers in the Infantry and Mechanical Maintenance CMFs with higher AFQT scores have higher post-service earnings; there is no relationship for administration personnel. A mechanic with AFQT 65, for example, is estimated to have about 7 percent higher earnings than an otherwise similar mechanic with an AFQT of 35.

We find a strong, positive relationship between a soldier's grade at separation, relative to his accession cohort, and post-

service earnings. A soldier who is half a grade ahead of his or her cohort at the first-term reenlistment point, which places him or her in approximately the top 15 percent in terms of promotion speed, has earnings between 7 percent and 8 percent higher, depending on the occupation. One explanation for this finding is that civilian employers value in their employees the same characteristics that the Army uses for promotion. Another possibility is that the correlation is caused by sample selection. Suppose that the promotion process does not identify individuals who perform well in civilian employment. Because soldiers at higher grades have higher military earnings, only those fast promotees who are fortunate enough to receive unusually high post-service wage offers will leave, inducing a positive correlation between the relative grade variable and post-service earnings.

While we cannot rule out the sample selection argument, our promotion time models in Appendix C do support the interpretation that the Army promotes individuals who are likely to succeed in the civilian labor market. We find that promotion speed is positively related to aptitude test scores and years of education. If promotions are correlated with these two observable characteristics, which have consistently been found in the labor economics literature to be positively related to private sector earnings, then it seems plausible that promotions might also signal other desirable attributes we cannot directly observe, such as motivation.

In contrast to G-W, we find no significant difference between the post-service earnings of black and white soldiers in all three occupation groups, holding other characteristics constant. Differences in the specification of the earnings model—ours has more covariates—or the fact that our observations on earnings come from a period 10 years later than the data used by G-W may explain the difference in the findings.

We also find a large, negative earnings differential for female soldiers. With less than 1 percent of the sample being female, the result for the combat group may be anomolous. However, we also estimate that females in the mechanics-craftsmen and administration-supply groups have 40 percent lower earnings than otherwise comparable males. One pos-

sible explanation is that female soldiers are more likely to reduce their labor force participation when they separate from the military because of family commitments. However, when we reestimated the models including a dummy variable for females with dependents, the coefficient on the female variable dropped only marginally. In comparision with the results on the male-female earnings differential in the labor economics literature, these estimates are much too large, especially given that we control for occupation, on-the-job performance through the pay grade variable, aptitude in the AFQT score, and education.

Civilian Earnings Predictions

The civilian earnings predictions used in our ACOL variable are generated using a soldier's characteristics at ETS and the parameters in Table D-2. In order to predict full-time earnings, we set the first-year-out variable and the YOS index variables to zero. We also assume a constant unemployment rate in the predictions because unemployment is included as a separate explanatory variable in the reenlistment model. Finally, we do not use the female coefficients in the predictions because of the anomalous results. The predictions generated are in 1980 dollars; for reenlistment decisions in other years, we adjust the predictions for real growth in civilian earnings.[100]

Figure D-1 shows post-service earnings predictions, by year since accession, for soldiers in the combat occupation group who leave after 4, 8, 12, and 20 years of military service. In making these predictions, we assume the soldier is male, has a high school diploma, scored 50 on the AFQT, and is at the average grade for his accession cohort.

For each separation point, earnings increase with civilian experience but at a decreasing rate. Across separation points, there is an increase in initial earnings due to the additional military experience accumulated, but the growth in earnings with additional civilian experience (the slope of the earnings-experience profile) is smaller. Because of the low return to military work experience relative to civilian experience for the combat occupations, there is a substantial post-service earnings penalty associated with longer military careers. As com-

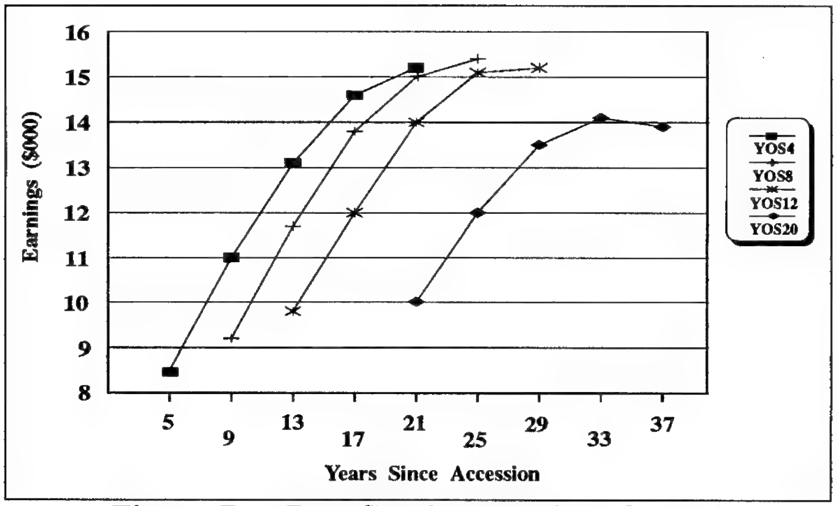

Figure D-1. Post-Service Earnings by YOS at Separation (Combat)

pared with the annual earnings of a soldier who leaves after the first term and accumulates civilian experience, a soldier separating with 20 years service earns about $5,000 (or 34 percent) less in his or her first year in the civilian sector.[101]

Figures D-2 and D-3 display predictions for soldiers in the mechanics-craftsmen group and the administration-supply group. In these occupation groups, the opportunity costs of longer military service are smaller because the returns to military work experience are greater.

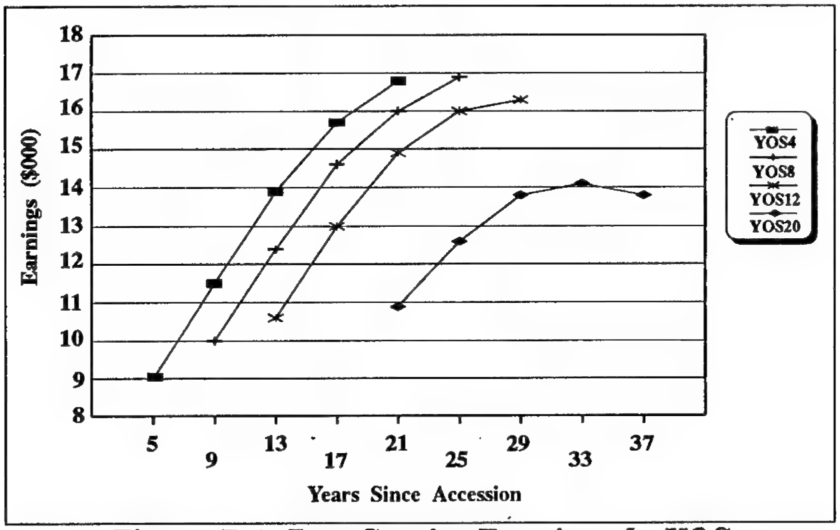

Figure D-2. Post-Service Earnings by YOS at Separation (Mechanics)

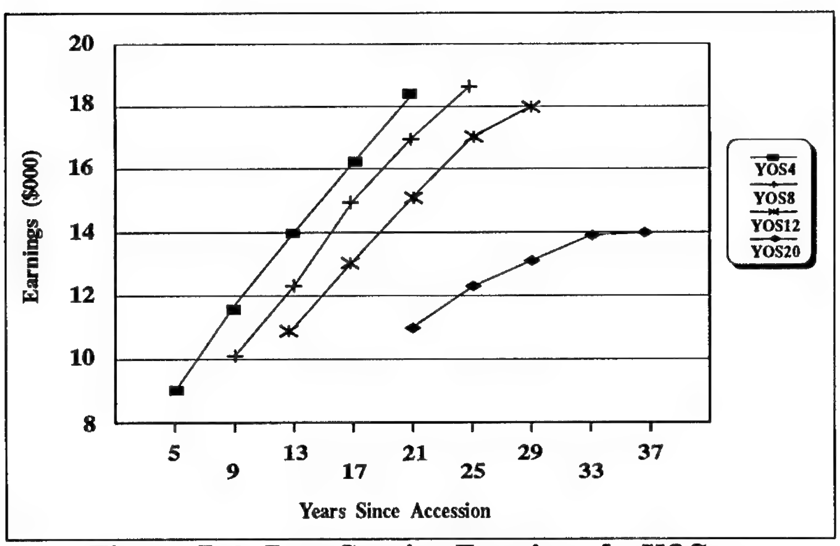

Figure D-3. Post-Service Earnings by YOS at Separation (Administration)

Appendix E: MOSs in Career Management Fields

CMF 11: Infantry

11B Infantryman
11C Indirect Fire Infantryman
11G Infantry Senior Sergeant
11H Heavy Antiarmor Weapons Infantryman
11M Fighting Vehicle Infantryman
11X Infantry Trainee
11Z Infantry Senior Sergeant

CMF 63: Mechanical Maintenance

41C Fire Control Instrument Repairer
41J Office Machine Repairer
44B Metal Worker
44E Machinist
45B Small Arms Repairer
45D Self-Propelled Field Artillery Turret Mechanic
45E M1 ABRAMS Tank Turret Mechanic
45G Fire Control System Repairer
45J Aircraft Armament Repairman
45K Tank Turret Repairer
45L Artillery Repairer
45M Aircraft Armament Subsystem Mechanic
45N M60A1/A3 Tank Turret Mechanic
45P SHERIDAN Turret Mechanic
45R M60A2 Tank Turret Mechanic
45T BRADLEY Fighting Vehicle System Turret Mechanic
45Z Armament/Fire Control Maintenance Supervisor
52A Powerman
52B Power Generation Equipment Operator Mechanic
52C Utilities Equipment Repairer
52D Power Generation Equipment Repairer
52F Turbine Engine Driven Generator Repairer
62B Construction Equipment Repairer
63A Mechanical Maintenance Helper
63B Light Wheel Vehicle Mechanic
63C Track Vehicle Mechanic
63D Self Propelled Field Artillery System Mechanic
63E M1 ABRAMS Tank Systems Mechanic
63F Recovery Specialist

63G Fuel and Electrical Systems Repairer
63H Track Vehicle Repairer
63J Quartermaster and Chemical Equipment Repairer
63K Quartermaster and Heavy Equipment Repairman
63N M60A1/A3 Tank System Mechanic
63R M60A2 Tank System Mechanic
63S Heavy-Wheel Vehicle Mechanic
63T BRADLEY Fighting Vehicle System Mechanic
63W Wheel Vehicle Repairer
63Y Track Vehicle Mechanic
63Z Mechanical Maintenance Supervisor

CMF 71: Administration

03C Physical Activities Specialist
71B Clerk-Typist
71C Executive Administrative Assistant
71D Legal Specialist
71E Court Reporter
71F Postal Clerk
71L Administrative Specialist
71M Chaplain Assistant
73C Finance Specialist
73D Accounting Specialist
73Z Finance Senior Sergeant
75B Personnel Administration Specialist
75C Personnel Management Specialist
75D Personnel Records Specialist
75E Personnel Action Specialist
75F Personnel Information System Management Specialist
75Z Personnel Sergeant

Notes

1. Although the literature on Army reenlistment behavior is limited, there are many studies for enlisted personnel in the other services, particularly the Navy. We discuss the relevant studies in the context of developing the reenlistment model.

2. There are also more mundane, but potentially important, specification issues caused by the fact that reenlistment is not a dichotomous process as the ACOL model assumes. For example, soldiers may reenlist before the end of their term, extend their term of service rather than reenlist, and reenlist for retraining in a new occupation. How a multiple-choice process is condensed into a dichotomous choice may affect the parameter estimates.

3. A more general formulation of the choice model would also consider the riskiness of different forms of compensation. Daula (1981) and Hausman (1984) discuss reenlistment models that incorporate this factor.

4. A sequential decision rule, which compares military and civilian compensation over the next term, is not appropriate because expected compensation beyond the next term depends on the current decision.

5. Daula and Moffitt (1989) estimate a dynamic programming model of reenlistment that addresses both the discount rate and single horizon issues.

6. To simplify the notation, the "maximum" on the ACOL variable is assumed.

7. In this discussion, we assume there are no Xs in the model.

8. For any one decision, we still assume that the relative nonpecuniary returns to a military career are constant over the planning horizon. The difference is that equation (10) allows the evaluation of those returns to be modified at each decision point.

9. In our empirical work, the majority of these censored observations are the result of missing data due to the end of the observation period.

10. With three or more decisions, it becomes impractical to directly use the appropriate multivariate normal distribution to

specify the stay and leave probabilities. In Black et al. (1985), where a series of 10 decisions were modeled, the probabilities are formulated as the product of period-by-period stay and leave probabilities. This model can be estimated with quadrature methods described in Butler and Moffitt (1982).

11. The only exception is if ρ equals 0, so that the joint probability of reenlisting at the first and second terms, the numerator in equation (12), is just the product of two univariate cumulative normal expressions.

12. A variation is to include the survival rate to the second-term decision point as a summary measure of the effect of all first-term variables.

13. The EPRDB is described in more detail in Appendix B. Other data sources, such as the file used to estimate post- service earnings, are described below or in one of the appendixes.

14. The MOSs included in each CMF are listed in Appendix E.

15. We do not count as attrition early separations with a separation code indicating a normal end of term, such as an early release.

16. We treat soldiers who leave early in their second term of service, a much smaller proportion than during the first, as censored after the first-term decision.

17. There are also age and citizenship requirements. See Army Regulation 601-280, "Army Reenlistment Program," for more details.

18. Using the ISC codes, we do eliminate soldiers who were separated for death, entry into officer programs, or serious behavioral infractions. However, this amounts to only about 1% of the sample for each CMF.

19. Brown (1990) estimates a two-equation, eligibility-intentions model to study how the first-term reenlistment process affects the average quality of the enlisted force.

20. The reduced form has the additional advantage of directly providing predictions of the unconditional reenlistment rate, which is what the Army requires for force-planning purposes.

21. Repeated extensions are possible. However, we cannot generally distinguish in the data between two 3-month extensions, for example, and one 6-month extension.

22. Education benefits can be used on active duty; however, most usage occurs after the member has separated.

23. Alternatively, we could calculate military compensation for a sample of soldiers and estimate a model of compensation as a function of those characteristics. As this necessarily summarizes the relationship between the components of pay and soldier characteristics found in the pay and allowance tables, it is likely to be less accurate than the method we use.

24. This result also implies that cross-sectional estimates of military compensation, which are based on the "survivors" at each grade, overstate expected military pay for the typical soldier at ETS. The size of the error, however, may be small as substantial differences in promotion times do not translate into large pay differences. The pay raises associated with promotions are relatively small, and there is a *negative* correlation between promotion times to successive grades (see below).

25. Even under this assumption, a soldier's relative military pay will vary over the planning horizon because of the different experience-earnings profiles in the military and civilian sectors.

26. VHA amounts vary with the geographic area to which a soldier is assigned. As higher-than-average VHA payments in the current assignment are likely to be followed by lower-than-average payments, and vice versa, we use the assignment-weighted average for all geographic areas for this allowance.

27. In a before-tax comparison of military and civilian compensations, allowances are worth more than their nominal amount because they are not taxed as income. Because of the lack of critical data required to calculate the tax advantage, such as spousal earnings and other family income, we do not make this adjustment.

28. The data set, our methodology, and the estimation results are described in greater detail in Appendix D.

29. Reductions in hours of work due to involuntary unemployment, which affect civilian but not military earnings, should be included in the reenlistment model. We follow the

literature and include the unemployment rate at the decision point as a separate variable.

30. Another possibility is that the correlation is caused by sample selection. However, the promotion time results, which show a positive correlation between promotion speed and AFQT and education, support the interpretation that fast promotions signal attributes desired by civilian employers.

31. Because of the effect of military retirement benefits, ACOLs for military careers longer than 20 years are less than at the 20-year point and, therefore, are not computed.

32. The latter category includes American Indians, Alaskan Natives, and Asian/Pacific Islanders.

33. Note that the effect may be attenuated when *all* soldiers are included in the model. With constant accession goals, the increase in high-quality enlistments associated with higher unemployment rates implies that a smaller fraction of other youths will be allowed to enlist. This may increase the average taste for military service among enlistees from this group.

34. When there is a choice of education benefits programs at enlistment, as is the case with the ACF, individuals signal their intentions to pursue post-service education by enlisting in occupations with higher benefits. With historical data, we cannot differentiate between the incentive and self-selection explanations for the effect of education benefits on reenlistment behavior. However, both arguments suggest a negative effect.

35. In most of the programs, a soldier's contributions are matched by government funds. Our variable measures the present value of the government contributions available with full participation by the soldier.

36. A very small fraction of individuals in our data enlist initially for five or six years. We exclude them from the analysis.

37. See the notes to Table 3.6 for the definitions of the MOS groups in each CMF.

38. For much of the observation period, soldiers with GEDs cannot be distinguished from high school graduates and are, therefore, assigned 12 years of education.

39. As our above discussion implies, the characteristics of the enlisted personnel in a unit, such as the distribution across occupations and initial terms, will affect the expected number of reenlistments, but these factors are not systematically considered in assigning goals.

40. These all-Army rates are from *Military Manpower Statistics, 1986.*

41. We use the Army definition of reenlistment eligibility to calculate this rate.

42. The unemployment rates are from the Current Population Survey.

43. We identify reenlistments in the DMDC data by looking for a change in the date of latest reenlistment. There is anecdotal evidence, however, that for certain years the date of latest reenlistment variable was incorrectly recorded. In a preliminary analysis, we reestimated our models including what appeared to be long extensions (change in the ETS date greater than 24 months but no change in date of latest reenlistment) as reenlistments. There was almost no difference in the results.

44. The sharp drop in sample sizes for the second-term decision is the result of four factors: the 60 percent separation rate at the first-term reenlistment point, the time censoring of the longitudinal records in FY 1987, CMF switching at the end of the first term, and attrition during the second term of service.

45. The AFQT scores we use were normed by giving the ASVAB test to the youth sample of the National Longitudinal Surveys in 1980.

46. Table A-1 in Appendix A displays means, by fiscal year, for soldiers in each CMF making first-term decisions.

47. These results are for infantry soldiers at the first-term decision point. The findings are similar for the other CMFs.

48. These results are also affected by an asymmetry in the specification of racial groups in the promotion and civilian compensation models, which was necessitated by the available data. In the former, there is a minority variable, which is defined to include black, Hispanic, and "other" race soldiers.

In the post-service earnings models, only blacks can be separately identified.

49. The reported standard errors do not take into account the stochastic nature of the military and civilian compensation predictions. In general, it is not possible to determine a priori whether the true standard errors would be smaller or larger than those reported, although previous experience with similar models suggests the latter result.

50. If the variance of the error distribution is different for the second-term decision, the estimated parameters will also vary (see equation 11). But, in this case, the ratio of the first- and second-term parameters should be the same, which is not what we find.

51. This is the same result found by Daula and Baldwin (1986).

52. Most of the second-term decisions in our sample occur after FY 1982, so we cannot adequately test for a difference across the periods in second-term reenlistment rates.

53. This argument is less convincing for second-term reenlistment decisions, which occur five to eight years after accession.

54. The reenlistment elasticity in our model varies with the composition of the military "pay" increase. Because the maximum ACOL horizon for most members of the sample includes retirement eligibility, an increase in basic pay (which affects the level of retirement benefits) has a bigger effect on the reenlistment rate, dollar for dollar, than an increase in allowances.

55. The results of this specification are reported in Table 7-3 of their paper.

56. An implication of these modest lagged compensation effects is that the simple ACOL model may be an adequate tool for projecting the short-term effects of compensation changes in policy analysis applications, such as force inventory models.

57. Note that the effect of different earnings specifications on the pay elasticity depends on the specification of taste factors. With the baseline set of taste variables, where more characteristics are being held constant, the effects are reversed. This interaction makes it particularly difficult to

predict how potential changes in the specification of earnings models would affect the pay elasticities reported in existing studies.

58. These pay elasticities are not different, in a statistical sense, from the pay elasticity estimated in the baseline model because the 95% confidence interval from that model includes elasticities from 0.6 to 2.0. But this is small comfort to the policymaker for whom these differences are large in a practical sense.

59. The independent probit, like the multinomial logit, assumes zero correlations between the errors associated with the utility value of different choices. This is probably not a realistic assumption in this situation where the reenlist and retrain options, in contrast to separation, both involve continued military service. However, we could not statistically identify the parameters of the covariance probit, the multinomial probit model, which relaxes this assumption.

60. The R's generated by this model converge to .904, not far from the 1974–87 average value of .922.

61. Sample selection bias is also a potential problem in our estimates of military pay. The hazard models we use in predicting promotion times, however, do adjust for the censoring that occurs from separations between promotion points (see Appendix C).

62. See the discussion of sample selection bias in Appendix D.

63. This is the approach typically used in modeling enlistment supply where the services enlist as many high-quality individuals as possible but limit the enlistments of others.

64. Unlike previously reported results, these are simple probit models. There are not enough second-term decisions in the early period to estimate joint models.

65. If we drop education, AFQT, and relative pay grade from the infantry model, however, the first-term pay elasticity for the all-at-ETS sample is approximately half that estimated with eligibles only.

66. The EPRDB is being augmented to include accessions and EMF data through FY 1988.

67. Note that the variable definitions change over time, and all variables are not available for all years. Consult Noznisky et al. (1990) for additional information.

68. The data source for Basic Pay, BAQ, and BAS rates is the *Uniformed Services Almanac*, published annually by Uniformed Services Almanac, Inc.

69. Pay for years in which promotions occur are a weighted average of pay at the two grades, with the weights determined by when in the year the promotion occurs.

70. Three rates are available: (1) Full Rate Without Dependents, (2) Partial Rate Without Dependents, and (3) With Dependents Rate. We use rates (1) and (3) for soldiers without and with dependents, respectively.

71. The all-DoD averages are published in the annual DoD Military Compensation books starting in FY 1982. First-year program data (FY 1981) was not published but is estimated using FY 1982 data adjusted by the change in the GNP deflator.

72. The Bonus Extension and Retraining (BEAR) Program, in which bonuses were paid to reenlisters retraining in certain shortage MOSs, is one exception.

73. Note the distinction between promotion-time, which we define as the months required to advance from one grade to the next, and time in service at promotion to a given grade, the sum of promotion times up to that grade.

74. Censoring bias in promotion time models is also a potentially important issue in predicting military pay. We want unbiased predictions of future promotion times for all soldiers making a reenlistment decision, not just those who remain in the Army.

75. An interesting test of the maintained hypothesis in the D-N analysis is found in Tan and Ward (1985). They develop a multiple-indicator, multiple-cause model in which the relationship between unobserved performance and promotion times can, under the appropriate assumptions, be measured.

76. In 1980, some individuals had been an E-4 or E-5 for more than a year. Although the date of their promotion to this grade was known, they were treated as front-censored in the

estimation procedure because the values for the explanatory variables were not observed at the promotion point.

77. The D-N promotion time models are used to predict military earnings in Daula (1984) and Baldwin and Daula (1986).

78. The data set from which these results are calculated is described below.

79. We have presented the model as a censored, log-normal regression, with censoring points that vary with the observation. This is a reparameterization of the log-normal hazard model described in Kalbfleisch and Prentice (1980).

80. Demotions account for approximately 10 percent of the observations on E-5 promotions for the Infantry CMF and 5 percent for the others.

81. It is worth noting that errors in predicting promotion times to the senior grades, as compared with errors for the junior grades, have a smaller effect on the ACOL variable at the first- and second-term decision points because of the discounting of future military compensation.

82. As the dependent variable in these models is the natural logarithm of months to promotion, the coefficients can be interpreted as the proportionate change in promotion times associated with a unit change in the explanatory variable.

83. In these predictions, we assume the soldiers were both promoted to E-3 at one year of service, are nonminority males, have a high school diploma, have no dependents, and enlisted in FY 1983. We also assume that both soldiers are serving in the same MOS and, therefore, do not include a reenlistment bonus in the calculations.

84. There is also a large literature on a topic closely related to the task of predicting post-service earnings, the effect of veteran status on civilian earnings. See Martindale and Poston (1979), Berger and Hirsch (1983), Little and Fredland (1979), DeTray (1983), and Crane and Wise (1987), among others.

85. An individual's earnings are only reported to SSA up to the limit for which Social Security taxes are collected.

86. Because of the quadratic specification, experience effects vary with the number of years of experience. In this

appendix, we will discuss experience effects evaluated at the first year.

87. Ross and Warner (1976) find that, at most, only between 20 percent and 30 percent of veterans took civilian jobs similar to their military occupations.

88. With the sample selection correction, the post-service earnings model can be written as $Y_i = X_i\beta + \eta\sigma_\varepsilon(\phi/\Phi)$, where η is the correlation between the errors in the separation and earnings equations and Φ is the probability of separation. The bias in the estimated β_i from omitting the selection correction is $\eta\sigma_\varepsilon\delta_i$, where δ_i is the coefficient on X_i in the regression of ϕ/Φ on the X's. If those soldiers with the best earnings opportunities leave the Army, η will be positive. Thus, the sign of the bias is determined by δ_i, which will be positive if X_i is positively correlated with the probability of reenlistment.

89. The identification issue is complicated by the fact that the reenlistment data set, soldiers making reenlistment decisions in 1975 through 1980, is different from the earnings data. Thus, Daula's earnings model is truncated rather than censored, which is the usual situation in a sample selection model.

90. To our knowledge, the only other analysis using this data set is Cooper (1983). Cooper's analysis, however, is not directly relevant to our study because he combines the PSEHF data with Census data to estimate veterans' earnings differentials.

91. The PSEHF is described in Johnson (1983).

92. The original PSEHF includes only IRS data for 1979 through 1981. The additional two years of IRS earnings are in a supplement to the file.

93. Grouped data models are, of course, subject to aggregation bias. We believe that, in this case, this is the lesser of two econometric evils.

94. We do, however, estimate a reenlistment model that does not require post-service earnings projections, a limited test of the potential effects of sample selection bias.

95. In a preliminary analysis, Brown (1988) found that IRS average earnings, calculated without earnings at or above the SSA limit, were higher than the SSA averages, calculated with

the same restriction. Note that both the SSA and IRS earnings in the PSEHF exclude self-employment income.

96. The index variables run from 1 to the number of years in each interval. An alternative way to eliminate these potential biases is to estimate the model only for soldiers who separate with less than 13 years of service. This is not feasible here because we need to be able to predict post-service earnings at the 20-year point in order to calculate the ACOL variable.

97. As the dependent variable is expressed in natural logs, coefficients in the model show the proportionate change in earnings with a unit change in the associated explanatory variable.

98. In results not reported here, we included a "second year out" variable but found that the coefficient was not statistically significant.

99. We tried substituting a retirement annuity variable, like that used by G-W, for our YOS variable but obtained the same results.

100. We use annual earnings of all workers 16 and over from the Census Current Population Series to construct a real wage index.

101. This is similar to the difference estimated by Borjas and Welch (1986) using the 1977 DoD Retiree Survey.

Comment

David K. Horne
Roy D. Nord

As reviewers we have been involved with monitoring this contract, and many of our comments have been addressed in one way or another throughout this project. Possibly in spite of this, the paper by Smith, Sylwester, and Villa represents a valuable contribution to the military retention literature. The primary methodological contribution is the allowance for time-varying heterogeneity in the taste distribution. This addition eliminates the problem created when it is assumed that the taste distribution is truncated at the first reenlistment point. The implication of this assumption is that if all those who reenlist have sufficiently positive tastes to decide to reenlist at the end of the first term, the reenlistment rate among eligibles *after* the first term would be expected to be 100 percent. Under the original assumptions, the only possible reason for a decision to leave at the second reenlistment point, for instance, would be if the maximum ACOL occurs between the first and second reenlistment points. This is inconsistent with the empirical results. The solution is to allow tastes to include two components—one time invariant and the other variable over time.

The paper also provides extensive documentation on the stability of the retention model parameters, as well as tests for sensitivity arising from variations in discount rates, time horizons, and the eligibility of soldiers. These comments primarily deal with the data problems and policy issues inherent in retention modeling in general, which have implications for interpreting the current research effort.

Perhaps the most intractable issue in retention research is controlling for the demand for reenlistments. Army retention policies change from day to day. Some changes, such as variations in reenlistment bonuses, can readily be identified, although historical data are often difficult to obtain. However, most retention policy changes are impossible to identify, much less quantify. Retention goals change frequently, and as Smith et al. note, even the definition of goals (as a minimum versus a

maximum) varies. Retention goals are also a function of the recruiting environment. When recruiting is difficult, a constant-force end-strength can be maintained by increasing retention rates, as has been done recently.

One potential solution to controlling for Army demand is to limit analysis to soldiers eligible for reenlistment. However, eligibility is endogenous. Soldiers considered ineligible can often have bars to reenlistment removed by a number of actions. When the supply is limited, some ineligibility conditions can be waived. Smith et al. investigate using both eligibility and quality standards as ways to account for the endogeneity.

There is some evidence that a significant change in retention policy occurred in 1983. Due to a misnorming of the AFQT in 1979–1980, a large number of low-AFQT soldiers were inadvertently allowed to enlist. As these cohorts reached their point of reenlistment, the Army used a number of methods to screen out relatively poor performers. Reenlistment rates for the full ETS sample (completing the initial term of service) decreased 25 percent in the post-1982 sample (Table 3.14 in Smith et al.). The reenlistment rates for eligibles as well as high-quality soldiers also decreased by approximately the same percentage. These decreases reflect Army policy to limit the number of soldiers reenlisting from 1983 through 1985. In addition to implementing a ceiling on the numbers, numerous policies were implemented to screen soldiers at the point of reenlisting. For the first time, all soldiers at the first reenlistment point were required to appear before reenlistment screening boards, which included the battalion commanders. Initial term quality points were implemented, with a cut-off required for reenlistment qualification. All soldiers were required to meet weapons qualifications. Waivers that would allow reenlistment for unqualified soldiers were significantly suppressed. The grade ineligibility point for soldiers at grade E-4 was dropped from 10 to 8 years. The result was that soldiers holding the rank of E-4 at the end of their initial tour were restricted to reenlistment periods that would result in total time in service of eight years or less. This policy shortened the length of the reenlistment contract for many soldiers. Weight standards were tightened, the physical training test was revised, and a formal waiver was required for any soldier

who had been issued an Article 15 (for conduct unbefitting a soldier).

These Army policies had several effects on retention. First, fewer soldiers who reached the end of the initial tour were eligible to reenlist. With lower eligibility as well as fewer waivers, the reenlistment rates fell. These policies also increased high-quality soldiers as a percent of the total reenlistment group.

Smith et al. find that the coefficient for the quality variable in the retention equation increases in the post-1982 period and attribute that increase to changes in tastes and resulting queues to reenlist. However, there may be other interpretations for this phenomenon, specifically changes in reenlistment policies described above. Screening would have the effect of increasing reenlistment queues. The screening would be particularly relevant for soldiers who performed poorly relative to their enlistment cohort. Soldiers who desired to enlist, and who most likely would have previously been allowed to enlist in the earlier period, were now found to be ineligible. The retention process itself is also likely to be changed. Whereas in the earlier periods reenlistment NCOs were required to encourage as many soldiers as possible to reenlist, and had a variety of inducements to offer the soldier, this role shifted after 1982. In the later period, the NCO was responsible for screening out poor performers. The impact on high-quality soldiers is less obvious. The ceilings on the number of reenlistments and the shift in the primary role of reenlistment NCOs from sales to screening may have had a negative impact on the reenlistment rate among high-quality soldiers. Although it is likely that soldiers with good performance records were still encouraged to reenlist, the decrease in the reenlistment rate for the high-quality soldiers implies some negative impact of the policies on the retention of this group.

The reenlistment policy changes could have repercussions for the parameter estimates of the model. The total number of soldiers reenlisting after 1982 is likely to be demand constrained. In that case, the parameter estimates do not yield supply effects; the supply curve for total reenlistments cannot be identified. It is doubtful that the supply curve can be

identified even for high-quality soldiers given the proportionate decline in the retention rates for this group. It should be noted that these reenlistment rates fell despite substantial pay increases of 11.7 percent and 14.3 percent in 1980 and 1981, respectively. In addition, it appears that the reenlistment process itself changed over time, as goals became ceilings rather than floors. These considerations indicate a structural change in the underlying retention model.

If such demand constraints and changes in the structural model were experienced, the implications for the model are clear. Despite the appeal of time-series variation in compensation to identify the pay elasticity, it is inappropriate to pool observations from both periods into a single model if the structural model has changed. However, estimates based solely on the later period are likely to be unreliable if the supply curve cannot be identified.

One way to test the model and to enhance the credibility of the parameter estimates might be to test the forecasting ability of the model as more data become available. This would provide some preliminary evidence as to whether the structural parameters of the model have shifted over time, and whether the small policy changes that occur frequently will have the effect of distorting the predictions of the model.

On a slightly different note, the use of predicted promotion times derived from a model of promotion, rather than average promotion time, is a significant step forward in modeling retention. Although promotion times are modeled at the CMF level, there are often substantial differences in promotion times within a CMF at the MOS or skill levels. However, it might be appropriate to account for average differences in promotion times at the MOS level. The key source of within-CMF variation is differences in promotion opportunities (demand) within MOS. It might be possible to model these differences without cluttering the specification with dummy variables by simply including the average rate of promotions in the MOS as an explanatory variable.

Smith et al. note that the promotion times have a relatively small impact on the retention model. Promotion times appear to have a small positive effect on military earnings, a larger

positive effect on nonpecuniary rewards to military service, and (apparently) a relatively large positive effect on civilian earnings. Some of this effect on civilian earnings may be due partially to the selection bias; those who separate from the military are likely to have higher civilian wage offers than those who remain in the service. This means that the net effect on ACOL is small and negative, the result of large increases in civilian opportunity minus small increases in military compensation. This negative effect, however, is offset to some degree by the net increase in nonpecuniary rewards from fast promotion. The final result is insignificant in the reduced form model.

We would expect that the impact of pay would be similar for the first and second reenlistment point. This, as pointed out in the paper, is consistent with the economic theory and would be predicted given the correction for sample selection. However, the equality constraints on the joint model are rejected. The interpretation of this finding is not clear. However, it is somewhat worrisome to find a key prediction of the theoretical model rejected empirically. Smith et al. do note the inconsistency between the empirical results and the theory. Additional investigation should be pursued to identify the underlying problems, and whether the theory, model specification, or estimation procedures need to be modified.

The civilian earnings of veterans is, of course, critical to identifying the impact of changes in pay. Better information on civilian earnings is needed, but there is a paucity of such data. There are several drawbacks to the DMDC Post-Service Earnings History File as discussed in the paper. Not only would more recent data be useful, but individual data with information on labor supply rather than total earnings would be valuable. Poor data on civilian earnings of veterans will continue to limit research in military manpower in the coming years if new data sources are not developed.

In summary, the paper by Smith, Sylwester, and Villa is well done and provides a great deal of insight into the reenlistment process. The sensitivity of the empirical models to a host of specification issues is also investigated. Further research, particularly as more cohorts are added to the data set over time,

might be devoted to an investigation of the implications of the demand constraints and possible structural shifts in the post-1982 period. The problem with the changes in the pay effect across reenlistment points should also be resolved in future research.

The precision of the coefficient estimates in the retention model are limited by the quality of the data. Specifically, better data are required on the civilian wages of veterans. Improved data are also needed on the many changes in Army policies that affect the retention of soldiers. The acquisition and maintenance of the requisite data bases would require additional resources, but the expected return on such an investment is large. Substantial resources are devoted to recruiting and retaining manpower to maintain the Army's active enlisted end-strength. Even small improvements in the accuracy of estimates for pay, bonuses, retirement, policy changes, and demographic changes would yield large cost savings by increasing the efficiency with which these manpower resources are managed.

4

Estimating a Dynamic Programming Model of Army Reenlistment Behavior

Thomas V. Daula
Robert A. Moffitt

I. Introduction

In the last several years, advances in techniques for estimating discrete-space dynamic programming models of individual behavior have advanced considerably (see Eckstein and Wolpin, 1989, for a review). Most of the applications to date have been in the area of labor economics, but there have been studies in industrial organization and other fields. Nevertheless, while several such models have been estimated, the limits to further development are in large part computational in nature. Even simple models of the type estimated thus far require extensive numerical calculations in solving the dynamic program involved and are usually embedded in an iterative maximum likelihood estimation procedure as well.

In this paper we demonstrate a method for estimating a simple dynamic programming model with a relatively economical computational technique. In a simple model of optimal stopping behavior we demonstrate an iterative estimation method in which the solution to the dynamic program alter-

nates with a simple probit estimation of a stopping function. The solution to the dynamic program thus takes place outside the probit estimation step, simplifying the estimation procedure and providing savings in computational effort.

Our application is to reenlistment behavior in the U.S. Army. Reenlistment behavior in the Armed Services is an important area of research, for the Services must use retention to maintain a viable force since lateral accessions are not possible, as they are in most other major organizations. However, while there have been several studies of the effects of pay, bonuses, and retirement incentives on reenlistment behavior in the Navy and the Air Force, there have been few studies of the U.S. Army. Thus, our study contributes to a new literature on Army reenlistment.[1]

In the next section we briefly review the background literature on military reenlistment relevant to our study and in the following section we present our dynamic programming model. We discuss our data on Army infantrymen in the subsequent section, followed by our estimation results. A summary and conclusion ends the paper.

II. Background Literature

Much of the literature on Army reenlistment behavior dates from the inception of the All-Volunteer Force, or AVF (for general literature reviews, see Daula, 1981; Daula and Smith, 1985; and Polich et al., 1986). In the first generation of these models, aggregate data were used to estimate the determinants of reenlistment rates as a function of the presence of reenlistment bonuses and other policy measures. Subsequently, a second generation of models was developed that used richer individual data to estimate the effects on reenlistment of more detailed variables such as military pay, bonuses, retirement benefits, and nonpecuniary aspects of military life (Warner and Simon, 1978; Goldberg and Warner, 1982; Baldwin and Daula, 1985b).

For our purposes, the most relevant aspect of these second-generation models is their treatment of the dynamic nature of the process and their assumptions regarding the time horizon for reenlistment decision making. Some assumption is essen-

tial to any reenlistment model because the specification of the reward to reenlistment requires an assumption regarding an individual's expectation of future time in the military. In some of the studies, a simple four-year horizon was assumed, particularly studies of the effects of bonuses. In a preferable treatment, other studies developed the annualized cost of leaving, or ACOL, model, which assumes that individuals calculate the value of staying in the military on the basis of a single optimal future military leaving date. We will discuss this model in more detail below, inasmuch as we view it as the major alternative methodology to ours in this literature.

The model whose methodology is most closely related to ours is that of Air Force officer retention of Gotz and McCall (1984). The Gotz-McCall model is a dynamic programming model of the type we develop below. However, because of difficulties of computation, their model was estimated only in a very highly restricted form—a parameter space of only size three, a fixed discount rate *a priori*, no exogenous covariates, and no computed standard errors. Our interest in economical computational methods is in part motivated by the apparent difficulties experienced by Gotz-McCall in the only attempt at dynamic programming estimation in this literature prior to ours.

III. Dynamic Programming Model of Reenlistment Behavior

In our exposition of our model and its estimation, we shall first lay out the simplest form of the model to help make the key points. Following that exposition, we will introduce several complicating factors, which we take into account in light of our specific application.

Assume that an individual finishing his first term in the military is considering whether to leave the military for the civilian sector or to reenlist. We assume that he may not return if he leaves, and that he consequently expects only civilian earnings if he does not reenlist. If he does reenlist, he must form expectations of when he will leave the military in the future. These expectations will be assumed to be optimally formed. We also assume a finite horizon.

Letting "L" denote the choice to leave and "S" the choice to stay, the present values of leaving and staying, respectively, can be written as follows:

(1) $$V_t^L = W_t^c + \sum_{\tau=t+1}^{T} \beta^{\tau-t} W_\tau^c + \varepsilon_t^c$$

(2) $$V_t^S = W_t^m + \beta E_t (V_{t+1}) + \varepsilon_t^m$$

(3) $$V_{t+1} = \max (V_{t+1}^L, V_{t+1}^S)$$

Where V_t^L and V_t^S are the respective present values of leaving and staying at time t, W_t^c and W_t^m are the respective period-t incomes in the civilian sector and the military—which include not only base pay in the military but also bonuses, and which include retirement pay as well—ε_t^c and ε_t^m are two error terms, β is the discount factor, and T is the length of the horizon. The key assumption in (2) is that the value of reenlisting depends upon the value of continuing to follow optimal behavior in the future, as defined by (3).

For given values for the pay streams and for known values of β and the parameters of the distribution of the error terms, the dynamic program implicit in (1)–(3) can be solved by backward recursion. This solution can be embedded in a maximum likelihood procedure in which the probabilities of observing reenlistment choice for each individual are specified as a function of the parameters in the problem as they enter into the solution. Iteration over those parameters can then take place by re-solving the dynamic program for each trial value of the parameters and by recomputing the probabilities of reenlistment choice.

Our computational simplification is based upon a particular expansion of (1)–(3). Solving equation (2) forward to the horizon point T can be seen to allow the model to be written in the following form:

(4) $$S_t = 1 \text{ if } S_t^* \geq 0 \text{ (stay)}$$
$$S_t = 0 \text{ if } S_t^* < 0 \text{ (leave)}$$

(5) $$S_t^* = V_t^S - V_t^L$$

$$= a_t + \varepsilon_t$$

where, assuming $\varepsilon_t \sim N(0,\sigma_\varepsilon)$ and f and F are the unit normal p.d.f. and c.d.f., respectively,

(6) $$\varepsilon_t = \varepsilon_t^m - \varepsilon_t^c$$

(7) $$a_t = W_t^m - W_t^c + \sum_{\tau=t+1}^{T} \beta^{\tau-t} r_\tau (W_\tau^m - W_\tau^c) + \sigma_\varepsilon \sum_{\tau=t+1}^{T} \beta^{\tau-t} r_{\tau-1} f_\tau$$

(8) $$f_\tau = f(a_\tau/\sigma_\varepsilon)$$

(9) $$r_\tau = \prod_{m=t+1}^{\tau} \mathrm{Prob}(S_m^* \leq 0) = \prod_{m=t+1}^{\tau} F(a_m/\sigma_\varepsilon)$$

= probability of staying at least until τ

Equation (5) shows the reenlistment-choice equation to be expressed as a conventional probit equation with nonstochastic component a_t and normal error ε_t. The nonstochastic component, a_t, is seen in (7) to equal the sum of the contemporaneous pay difference and a weighted sum of future pay differences. Each future pay difference is weighted not only by the discount rate but also by r_τ, the probability that the individual will still be in the military at that time. The third term in (7), a weighted sum of means of future truncated normal error terms, arises because the individual always picks the maximum of V_t^L and V_t^S and hence has an above-zero expectation of ε_t.

Writing the model in this way permits us to estimate the model by a simple iterative procedure involving (i) calculation of values of r_τ using (9) and (7), followed by (ii) probit estimation of equation (5). In step (i), beginning with trial values of the unknown parameters (only β and σ_ε for the present), the dynamic program can be solved by backward recursion to generate the a_τ for each future τ and therefore to generate values of r_τ. In step (ii), these probabilities of leaving are treated as fixed constants in the probit estimation of (5), where now the RHS of (5) is specified as in equation (7) using the prior estimates of r_τ.[2] Estimation of (5) requires a nonlinear probit algorithm because the two parameters enter it nonlinearly, even

conditional on the r_τ, but this poses no computational difficulty. Alternating this probit estimation step with the calculation of new values of the r_τ from the prior step generates maximum likelihood estimates of the model. The computational savings obtain from not having to re-solve the dynamic program in the process of estimating equation (5) by probit.[3,4]

A vector of exogenous covariates can be added to the model as well. The simplest method of doing so is to allow the vector to represent determinants of nonmonetary differences or unmeasured monetary differences in the rewards to the military and civilian sectors and therefore to add them to the pay difference, $W_\tau^m - W_\tau^c$. Letting X be a row vector of characteristics and δ be its associated coefficient vector, the only modification required in the model is to equation (7), which now becomes

$$\text{(10)} \qquad a_t = W_t^m - W_t^c + X\delta + \sum_{\tau=t+1}^{T} \beta^{\tau-t} r_\tau (W_\tau^m - W_\tau^c + X\delta) + \sigma_\varepsilon \sum_{\tau=t+1}^{T} \beta^{\tau-t} r_{\tau-1} f_\tau$$

The unknown parameters in the model are now β, σ_ε, and δ. To simplify the estimation slightly, we set $\psi = 1/\sigma_\varepsilon$ and $\tilde{\delta} = d/\sigma_\varepsilon$ and rewrite (10) equivalently as

$$\text{(11)} \quad a_t/\sigma_\varepsilon = \psi(W_t^m - W_t^c) + X\tilde{\delta} + \sum_{\tau=t+1}^{T} \beta^{\tau-t} r_\tau [\psi(W_\tau^m - W_\tau^c) + X\tilde{\delta}] + \sum_{\tau=t+1}^{T} \beta^{\tau-t} r_{\tau-1} f_\tau$$

Thus, we estimate a coefficient on the military-civilian pay difference directly.

Two complicating factors in the military reenlistment application must be taken into account. First, it is widely recognized that military training gives the enlistee skills that are useful in the civilian sector to some extent. Consequently, the value of civilian wages will differ depending upon the length of time spent in the military. The model heretofore assumes that the civilian wage profile is invariant to the time of leaving from the military.

Second, departure from the military is difficult at any time other than the point at which a term is exhausted. We shall assume, therefore, that there are discrete decision points that occur every several years, depending upon the length of term, and that an individual who reenlists at one decision point will stay until the next decision point with probability one.

To incorporate the first complication we specify civilian earnings W^c_{st} to equal the civilian pay to be had at time t if the individual's last period in the military is s. To incorporate the second complication, we assume that the decision points for the individual are t_i, i = 1, ... n. With this notation, the values of leaving and staying at decision point t are, respectively,

$$V^L_{t_i} = W^c_{t_i-1,t_i} + \sum_{\tau=t_i+1}^{T} \beta^{\tau-t_i} W^c_{t_i-1,\tau} + \varepsilon^c_{t_i} \tag{12}$$

$$V^S_{t_i} = \sum_{\tau=t_i}^{t_{i+1}-1} \beta^{\tau-t_i} W^m_\tau + \beta^{t_{i+1}-t_i} E_{t_i}(V_{t_{i+1}}) + \varepsilon^m_{t_i} \tag{13}$$

$$V_{t_i} = \max(V^L_{t_i}, V^S_{t_i}) \tag{14}$$

Making the other modifications to the model noted above (i.e., renormalizing by σ_ε and adding an X vector), the model now becomes the following:

$$\begin{aligned} S^*_{t_i} &= V^S_{t_i} - V^L_{t_i} \\ &= a_{t_i} + \varepsilon_{t_i} \end{aligned} \tag{15}$$

where

$$a_{t_i} = \tilde{a}_{t_i} + \sum_{m=i+1}^{n} \beta^{t_m-t_i} r_m \tilde{a}_{t_m} + \sum_{m=i+1}^{n} \beta^{t_m-t_i} r_{m-1} f_{t_m} \tag{16}$$

$$\begin{aligned} \tilde{a}_{t_i} &= \sum_{\tau=t_i}^{t_{i+1}-1} \beta^{\tau-t_i} [\psi(W^m_\tau - W^c_{t_i-1,\tau}) + X\tilde{\delta}] \\ &+ \sum_{\tau=t_{i+1}}^{T} \beta^{\tau-t_i} [\psi(W^c_{t_{i+1}-1,\tau} - W^c_{t_i-1,\tau})] \end{aligned} \tag{17}$$

$$\varepsilon_{t_i} = \varepsilon^{m}_{t_i} - \varepsilon^{c}_{t_i} \tag{18}$$

$$f_{t_i} = f(a_{t_i}) \tag{19}$$

$$r_m = \Pi^{m}_{t=1} F(a_{t_i}) \tag{20}$$

The major difference in this model is shown in equation (17), where it is now seen that the reenlistment decision is based in part upon the change in civilian earnings that results from staying another decision interval in the military.

IV. Data

The data we use are drawn from a sample of individuals who enlisted in the infantry between FY 1974, shortly after the beginning of the AVF, and FY 1984.[5] The data tracks the individuals on an annual basis until 1987 or separation from the Army, whichever occurs first. We select a random sample of enlistees with at least a high school education and an Armed Forces Qualification Test (AFQT) score above the 50th-percentile point for our analysis and who became eligible for their first-term reenlistment decision by the end of the period. Our sample contains 597 observations.

The independent variables we use are drawn from the data base developed by Smith et al. (1990). Military pay profiles are estimated for each individual from military pay schedules by years of service and pay grade and from estimates of promotion probabilities over the military career. Military pay includes base pay, allowances for housing and subsistence, reenlistment bonuses, and a variety of other forms of special pay. Post-service pay for educational benefits and military retirement pay are also calculated and are included in the civilian pay stream in the appropriate location. Civilian earnings are estimated from data on the post-service civilian earnings of veterans, and a separate pay stream is estimated for veterans with different numbers of years of service, as the model modifications above discussed.

We assume that a reenlistee has decision points every four years after reenlistment up until his 20th year of service, when he becomes vested for military retirement benefits. After that point we assume annual decision points up to 29 years of service. We assume that all individuals who have not left by their 29th year do so in their 30th year. The actual number of decision points varies

from individual to individual in the sample because different individuals come up for their first-term reenlistment with different numbers of years of service.

For the X vector we include a number of variables available in the data: number of dependents, length of initial enlistment term, state unemployment rate at time of enlistment, a race dummy, score on the AFQT (given at enlistment), years of education at enlistment, and entitlement to educational benefits. We also include a dummy variable for whether reenlistment occurred after FY 1982, because reenlistment rates dropped sharply after that date for reasons not related to those in our model. Finally, we specify a variable equal to the difference between the individual's pay grade and the average pay grade for enlistees with the same number of years of service in order to capture differences across individuals in tastes for the military.

Means of the dependent variable and the X vector are shown in Table 4.1. Also shown is the mean of the contemporaneous military-civilian pay difference (i.e., the mean pay differential for the first year following the individual's reenlistment decision).

Table 4.1
Variable Means

Reenlistment rate	0.26
Contemporaneous pay difference (thousands)	0.53
Length of initial enlistment (years)	3.47
Number of dependents	0.51
State unemployment rate at enlistment	7.26
Armed Forces Qualification Test (AFQT)	71.77
Years of education at enlistment	12.21
Race (1 = black)	0.07
Educational benefits entitlement (1980 dollars in thousands)	5.40
Difference between individual pay grade and average pay grade	0.02
FY82 dummy (1 = reenlistment after FY 1982)	0.57

Sample size = 597.

V. Results

Basic Results

The first column of Table 4.2 shows the results of the estimation of the model. The estimate of the discount rate is .948, which implies an interest rate of approximately 6 percent. The coefficient on the pay difference ($1/\sigma_\varepsilon$) is positive and on the borderline of significance at conventional levels. The other variables in the equation show that reenlistment probabilities are significantly higher for those with more dependents, black enlistees, those with higher educational levels and with higher relative pay grades, and for those coming up for reenlistment prior to 1983.

The effects of each of the variables on reenlistment probabilities cannot be directly ascertained from Table 4.2 because each of the variables enters the reenlistment index function not only directly in the contemporaneous period but also in the difference expressions and retention probabilities at all future periods. To determine the effects of each, the change in the average reenlistment probability in the sample can be calculated in response to an increment in any one of the variables. For the pay difference, such a calculation indicates that a 10 percent increase in the pay difference increases the current reenlistment rate by three percentage points, or about a 12 percent increase in the probability. Thus, an elasticity of approximately unity is implied by the results. Increases in the X variables induce an average change in the reenlistment probability equal to approximately 2.5 times the indicated coefficient. Thus, for example, an increase in the education level at enlistment of one year would increase the reenlistment probability by approximately 7 percentage points. The results thus show fairly large reenlistment elasticities with respect to these variables.

The second column of Table 4.2 shows, for comparison purposes, the estimates of a naive probit model in which only the contemporaneous pay difference is included, along with the vector of X variables. Thus no forward-looking behavior is assumed. As the results indicate, the coefficients are by and large of higher significance level than in the dynamic programming model, a result to be expected since the parameters capture the "total" effect of a variable change. The magnitudes of the parameters

Table 4.2
Probit Coefficient Estimates

	Basic	Naive	Different Military and Civilian Pay
Discount rate	0.948*		0.963*
	(0.046)		(0.032)
Pay difference	0.376	1.033*	
	(0.230)	(0.042)	
Military			0.424*
			(0.132)
Civilian			−0.197
			(0.145)
Initial enlistment length	−0.010	0.119	−0.010
	(0.016)	(0.085)	(0.015)
Number of dependents	0.043*	0.267*	0.026*
	(0.013)	(0.065)	(0.013)
State unemployment rate	0.006	0.067*	0.007*
	(0.004)	(0.028)	(0.004)
AFQT	−0.000[a]	−0.006	−0.001
	(0.001)	(0.005)	(0.001)
Race	0.067*	0.507*	0.066*
	(0.031)	(0.205)	(0.028)
Educational level	0.031*	0.104	0.018
	(0.015)	(0.084)	(0.013)
Educational benefits	0.005	0.009	0.006
	(0.005)	(0.030)	(0.004)
Pay-grade difference	0.062*	0.140	0.024
	(0.031)	(0.117)	(0.028)
FY82 dummy	−0.045*	0.060	−0.058*
	(0.020)	(0.156)	(0.020)
Constant	−0.679*	−3.204	−0.791
	(0.261)	(1.175)	(0.155)
Log Likelihood Function	−314.55	−319.23	−313.20

Standard errors in parentheses.
*Significant at 10% level.
[a]Less than 0.0005 in absolute value.

cannot be compared, but the log likelihood values show roughly how much is gained by the forward-looking behavior incorporated in the dynamic programming model. As can be seen, there is a large decrease in the value of the log likelihood function in the second column.

The third column shows the results of allowing the military and civilian pay variables to have separate coefficients. The results show that the military pay coefficient is greater than the civilian pay coefficient. The coefficient difference is just significant at the 10 percent level ($t = 1.8$) and a likelihood ratio test also barely shows significance at the same level of confidence (statistic = 2.7, equal to the critical value). Thus, there is weak evidence for a difference in the effects of the two types of pay on reenlistment probabilities. The smaller civilian pay effect may stem from the greater uncertainty of the civilian pay stream. Although we have not incorporated uncertainty with the model, military pay streams are more certain and hence probably more highly valued.

We have also extended these results to incorporate the reenlistment decision at a second period. See Smith et al. (1990) for a more extensive analysis. Since such a model does not address the main methodological issues that we are addressing here, we have included those results as an appendix.

ACOL Comparisons

A popular alternative model for the estimation of reenlistment and retention probabilities is the ACOL model (see references in the introduction).[6] In the ACOL model it is assumed that an individual who is considering staying in the military determines a single optimal date of leaving, or a single optimal horizon, and then acts as if that date were certain. The optimal leaving date can be determined by calculating the present value of the lifetime income stream for each possible future leaving date—that is, by summing military pay up to each possible date and civilian pay thereafter—and by determining the date at which this sum is at its maximum.[7] Once this optimal leaving data is determined, it is assumed that the individual treats the present value of the lifetime income stream corresponding to this date as a regressor variable in a probit equation for reenlistment. The variable thus measures the present value of lifetime income if the individual stays in the military.

The chief advantage of the ACOL model is its computational simplicity. The determination of the optimal leaving date is made prior to estimation and hence no iteration is necessary over the lifetime income stream, unlike the dynamic programming model.

The ACOL model as implemented generally assumes a fixed value for the discount rate so as to make the calculation of the optimal leaving date possible, but this is not necessary to the technique.[8] Likewise, for simulation from the model, a change in a pay variable may be calculated prior to the use of the probit coefficient estimates for the prediction of policy effects.

In the context of our model, the ACOL model can be thought of as a model in which the values of the r_τ are set equal to 1 up to the optimal leaving date and equal to 0 at that date and thereafter. Thus, the ACOL model assumes the presence of certainty in a part of the dynamic programming model that allows uncertainty. However, the ACOL model is not nested in the dynamic programming model as we have specified it because no set of parameter values in our model will result in such a zero-one pattern of r_τ values. Consequently, there is no *a priori* reason for our model to yield the better fit.[9]

To compare parameter estimates and model fit of ACOL with our model, we estimate a version of the ACOL model that is as close to our model as possible in all respects save the key difference in assumptions regarding future uncertainty. To do this, we calculate the present value of the income stream for all possible leaving dates and thereby determine an optimal date, and we then estimate our model setting the values of the r_τ equal to 1 up to the optimal leaving date and equal to 0 at that date and thereafter. Since our estimation method already conditions on the values of the r_τ in one step of our iterative method, this is a relatively easy method to apply. Note that the parameters for σ_ε and $\tilde{\delta}$ still enter nonlinearly into our resulting probit equation, as shown in equations (16)–(17). To maintain comparability with past work as much as possible, we hold the discount rate fixed, pegging it at the value estimated with our dynamic programming model.[10]

Column (1) of Table 4.3 shows the distribution of optimal leaving dates in the sample. As the results show, almost three-fourths of the sample is predicted to choose to stay until the final decision point. Note that this point is at 29, not 20, years of service. Table 4.4 shows the probit estimates of the ACOL model using these optimal leaving dates to determine the r_τ values. Although the signs of the significant coefficients

Table 4.3
Distribution of Optimal ACOL Leaving Dates

No. Periods[a]	Baseline Model	All Wages Up by 10%	Constant Military Wages After 20 Years of Service
0	72.0	72.0	—
1	10.9	10.9	0.3
2	15.7	15.7	5.9
3	0.5	0.5	9.9
4	0.7	0.7	78.5
5	—	—	0.2
6	—	—	3.7
7	—	—	0.7
8	0.2	0.2	0.8

[a]No. of periods left before the final decision point (years-of-service = 29).

Table 4.4
Estimates of the ACOL Model

Pay difference	0.159* (0.049)
Initial enlistment length	–0.000[a] (0.006)
Number of dependents	0.023* (0.005)
State unemployment rate	0.004* (0.002)
AFQT	–0.000[a] (0.000)
Race	0.036* (0.015)
Educational level	0.016* (0.006)
Educational benefits	0.002 (0.002)
Pay-grade difference	0.025* (0.010)
FY82 dummy	–0.032* (0.012)
Constant	–0.348* (0.100)
Log Likelihood Function	–316.82

Standard errors in parentheses.
Discount rate = 0.948.
*Significant at 10% level.
[a]Less than 0.0005 in absolute value.

are the same as those in the dynamic programming model, and although the significance levels are not far different in the two, the magnitudes of the coefficients are quite different. The ACOL coefficients are generally considerably below those in the dynamic programming model, no doubt in part because those in the former model do not have an effect working through future retention probabilities and those in the latter model do.

Table 4.5 shows several goodness-of-fit statistics for the naive model, the dynamic programming model, and the ACOL model. As the results show, the dynamic programming model yields the best fit, the naive model the worst, and the ACOL model is in between in all cases.

Table 4.5
Goodness-of-Fit Statistics for Three Models

	Naive	Dynamic Programming	ACOL
Log Likelihood Function	319.23	–314.55	–316.82
Akaike Information Criterion[a]	330.23	326.55	327.82
Sum of Squared Residuals[b]	105.86	103.87	104.76

[a]Minus Log LF plus number of parameters estimated.

[b]Sum of squared deviations between reenlistment dummy and predicted reenlistment probability.

Table 4.6 shows the relative effects of two different changes in the pay profile. In the first, all pay levels are increased by 10 percent. Interestingly, this change has the largest effect on reenlistment probabilities in the ACOL model, even though such a change by definition has no effect on the optimal leaving date (see Table 4.3). The smallest response is in the naive model. In the second simulation, the military pay scale is held fixed (in real terms) after the 20th year of service. As shown in Table 4.3, this has a drastic effect in moving the optimal leaving date back toward earlier periods. As Table 4.6 indicates, once again the ACOL model shows much greater responsiveness to this change. While the dynamic programming

model implies virtually no response to the change, the ACOL model predicts a 1 percentage-point drop in reenlistment probabilities. Much of the difference in this simulation arises because the dynamic programming model implicitly estimates relatively low probabilities to surviving to decision points beyond the 20th year of service; hence a change in military pay in those years has little effect. In the ACOL model, on the other hand, many optimal leaving dates still fall in that period and hence military pay in that interval has a larger effect on current behavior.

Table 4.6
Effects of Wage Changes on Mean Reenlistment Probability (percentage points)

	Naive	Dynamic Programming	ACOL
Increase in All Wages by 10%:			
Before	.265	.265	.264
After	.282	.297	.304
Change	.017	.028	.040
Constant Military Wage After 20 Years of Service:			
Before		.265	.264
After		.264	.254
Change		–.001	–.010

VI. Summary

In this study, we have demonstrated the estimation of a simple dynamic programming model of reenlistment in the military. Our major contribution is to demonstrate that there exists a relatively simple computational algorithm to estimate such a model and that it is well within the bounds of computational feasibility given current computer technology. The estimates we obtain for first-term reenlistment of infantrymen

are plausible, and we obtain an estimate of the discount rate of 6 percent.

We also compare our estimates to those from the ACOL model. While the ACOL model is yet simpler to compute than the dynamic programming model, we find that the ACOL gives a worse fit to the data than does the dynamic programming model. Surprisingly, however, we also find that the ACOL model predicts stronger effects of policy changes than does the programming model. Hence, our evidence suggests that the effects of policy changes on reenlistment rates may be smaller than those that would have been obtained using our version of the ACOL.

Acknowledgments

The authors would like to thank D. Alton Smith at Systems Research and Applications Corporation for help all along the way and Wilbert Van Der Klaauw at Brown University for research assistance.

Appendix A: Estimation of a Two-Period Model

Incorporating the decision at a second reenlistment point involves an extension of the model similar to that in the ACOL-2 model (Smith et al., 1990). At the second decision point, those individuals still in the Army are assumed to make a decision to stay or leave of exactly the same form as that made at the first decision point, the only difference arising from a shorter time horizon and different military and civilian income profiles in the future. However, rather than treating the two observations on successive reenlistment decisions by those who reenlist at the first decision point as independent observations, which would result in dynamic self-selection bias, an extra unobserved individual-specific taste error term is added to the model to pick up the self-selection. The only significant implications for this second error term are computational: it must be integrated out, which means that the model must be solved and implicitly estimated for several different values of that error term.

Table A-1 shows three different sets of estimates for our dynamic programming model on the two-period data. The first column shows the estimates of our model but fixes the discount rate at the value estimated in our one-period model. Comparing the estimates to those in the first column of Table 4.2, it appears that the estimates of the one-period and two-period models are fairly close. Virtually all coefficients that are significant in one specification are significant in the other, and most are of the same order of magnitude. The pay coefficient in the two-period model is slightly higher in value than that in the one-period model, but the t-statistic in both cases is just on the border of statistical significance at the 10 percent level.

The second column in Table A-1 shows the estimates when the discount rate is allowed to be a free parameter. In this case, the estimates become extremely unstable and implausible. The pay coefficient triples in magnitude and becomes highly significant and the other coefficients in the equation change by large amounts.

Table A-1
Estimates of Two-Period Model

	High-Quality Fixed Discount Rate	High-Quality Free Discount Rate	All Eligible
Discount rate	0.948[a]	0.681*	0.905*
		(0.189)	(0.062)
Pay difference	0.233	0.896*	0.234
	(0.167)	(0.379)	(0.151)
Initial enlistment length	0.004	0.035	0.015
	(0.015)	(0.040)	(0.015)
Number of dependents	0.035*	0.104	0.038*
	(0.014)	(0.053)	(0.015)
State unemployment rate	0.007*	0.021	0.001
	(0.004)	(0.015)	(0.003)
AFQT	–0.001	–0.002	–0.001
	(0.001)	(0.002)	(0.004)
Race	0.064*	0.192	0.070*
	(0.033)	(0.125)	(0.029)
Educational level	0.027*	0.070*	–0.000[b]
	(0.014)	(0.035)	(0.007)
Educational benefits	0.002	0.010	–0.004
	(0.005)	(0.012)	(0.003)
Pay-grade difference	0.043*	0.111*	0.058*
	(0.026)	(0.060)	(0.026)
FY82 dummy	0.032	–0.004	–0.096*
	(0.022)	(0.061)	(0.030)
Standard deviation of gamma	19.414*	5.753*	13.701*
	(1.364)	(0.995)	(0.829)
Constant	–0.632*	–1.757*	–0.188
	(0.235)	(0.742)	(0.117)
Log Likelihood Function	–344.3	–343.9	–1050.4
Number of observations	597	597	1500

Standard errors in parentheses.

*Significant at 10% level.

[a]Held fixed.

[b]Less than 0.005 in absolute value.

These results reflect a difficulty in identifying the discount rate in the data. As can be seen from the values of the log likelihood functions for the first two columns of the table, very little explanatory power is added by permitting the discount rate to be a free parameter. In fact, by a likelihood ratio test, no significant explanatory power is added.

The probable cause of this instability is in the small sample size of enlistees at the second period. Of the 597 high-quality infantrymen at the first decision point, only 44 are present at the second decision point. This is not a sufficient number to obtain a reliable estimate of the taste parameter and the discount rate at the same time. This is also reflected in the table in the instability of the standard error of the taste error term when the discount rate is released.

To address this problem, we present in column (3) estimates on all eligible, not just those of high quality. The sample size at the first term is 1,500 in this case, and there are 194 observations at the second term point. As the table shows, the estimates in this case return to values close to those in column (1) even when the discount rate is allowed to float. Thus, these estimates are consistent with our interpretation of the instability indicated in the second column results, and strengthen our interpretation that the first and third columns are the most reliable results.

Notes

1. This study is a part of a larger group of studies also examining Army reenlistment. The study closest to ours is Smith et al. (1990), with which our study was performed in conjunction.

2. We also use the a_τ to estimate fixed values of the f_τ.

3. At the end of the estimation, standard errors are obtained by computing the outer product of a numerically estimated first derivatives matrix, the latter of which is calculated incorporating the dependence of the r_τ on the parameters of the problem. Note that the entire procedure has some resemblance to the EM algorithm.

4. Hotz and Miller (1989) have recently demonstrated the conditions under which initial consistent estimates of the r_τ obtained from the data—and not from a formal solution of the dynamic program—can be used in this way to estimate the probit equation only once, thereby avoiding solution of the dynamic program altogether. However, their conditions are rather stringent and not required by our procedure.

5. The data are identical to those used by Smith et al. (1990) and were provided to us by Smith.

6. These issues and differences between the ACOL and dynamic programming models were recently discussed in an exchange between Black et al. (forthcoming) and Gotz (forthcoming).

7. The more usual method of implementing the ACOL model annualizes the present values, but this difference is not germane to the issues we wish to address.

8. It would not be difficult to perform a grid search over different values of the discount rate, calculating different optimal leaving dates for each value, and thereby allow the discount rate to be an unknown parameter.

9. Intuitively, the ACOL model will give a better fit if the variances of the error terms decline as an individual looks to dates further in the future. The ACOL model assumes those variances to be zero after the current period, whereas our model assumes current and future variances to be identical.

10. Note that the optimal leaving dates we calculate for the ACOL model implicitly set δ equal to zero. In our dynamic programming model, with nonzero δ, the implied optimal leaving dates should be calculated by including $X\delta$ in the present value calculations. To attempt to do so in the ACOL model would, of course, defeat its purpose of computational simplicity.

Comment

Matthew S. Goldberg

Introduction

Daula and Moffitt present an interesting and innovative analysis of reenlistment decisions of first-term Army soldiers. They use a dynamic programming framework similar to that employed by Gotz and McCall (1984). However, Daula and Moffitt offer three potential improvements over Gotz and McCall. First, they include covariates (explanatory variables) in addition to relative military/civilian pay. These covariates include paygrade, race, length of initial enlistment, number of dependents, unemployment rate, AFQT score, years of schooling, and educational benefits level. Second, unlike Gotz and McCall, they report standard errors for their parameter estimates.[1] Finally, Daula and Moffitt report an estimate of first-term soldiers' real discount rate.

Estimation and Identification

I believe that Daula and Moffitt have not yet realized the full potential of their approach. First, they have thus far estimated their model only through a single reenlistment decision point. An important feature of their model, which distinguishes it from the earlier ACOL model, is the specification of a permanent/transitory error structure. Yet the permanent and transitory errors cannot be separated in the absence of panel data. Instead, the two errors combine and the estimation problem reduces to a univariate probit model (albeit one in which the limit of integration is a nonlinear function of the unknown parameters).

In addition, I am skeptical of their ability to identify the discount rate using their data set. I view the concept of "identification" in two distinct ways. First, a parameter is *theoretically* identified if it is not functionally related to other parameters in the likelihood function. Under this definition, two parameters are *not* separately identified if they always appear in the likelihood function as a sum, product, or ratio. Second, a parameter is *empirically* identified if the likelihood function is strictly (and sufficiently) concave along the cor-

responding axis. To illustrate these concepts, a linear regression on X and X^2 is always theoretically identified, but is empirically identified only if the variance in X is sufficiently large to permit estimation of the quadratic effect.

I am concerned that their discount rate may not be distinguishable from the pay coefficient in the probit model. To take an extreme example, suppose that the income stream is constant over time, and that the time horizon is infinite. Then the present value of pay is just I/r. If δ denotes the pay coefficient, then the contribution of pay to the limit of integration in the probit model is $\delta I/r$. Clearly δ and r are not separately identified. An increase in r simply deflates the present value of pay, and the estimate of δ is inflated by the same percentage, leaving the ratio δ/r (and the pay elasticity) unchanged.

I recognize that this example represents at best a caricature of the Daula and Moffitt situation. Their income stream is not constant, and their time horizon is certainly not infinite. Yet their Table 4.4 (Daula and Moffitt, 1989) reveals essentially a constant pay elasticity (the range is 2.16 to 2.48) even for discount rates that range from 2.76 to 15 percent. Apparently, changes in the discount rate are largely offset by changes in the pay coefficient.

The identification of r and δ may be assessed empirically through the correlation between the estimates r^* and δ^*; this correlation is easily obtained from the inverse Hessian matrix. Bounded variances on these estimates (with no restriction on the correlation) do *not* guarantee that the two parameters can be distinguished. For example, the correlation sub-matrix

$$\begin{array}{ll} r: 10^{-1} & 10^{-2} \\ \delta: 10^{-2} & 10^{-3} \end{array}$$

indicates bounded variances, but a correlation of unity and a determinant of zero. This situation is depicted in my Figure 1, where a likelihood contour nearly degenerates from an ellipse to a positively sloped line segment. All points along the line segment are equally likely, and there is no basis for choosing among these points (i.e., no basis for locating unique parameter estimates).

The ability to identify r depends on the nature of the "experiment" implicit in the data set. The income variation in

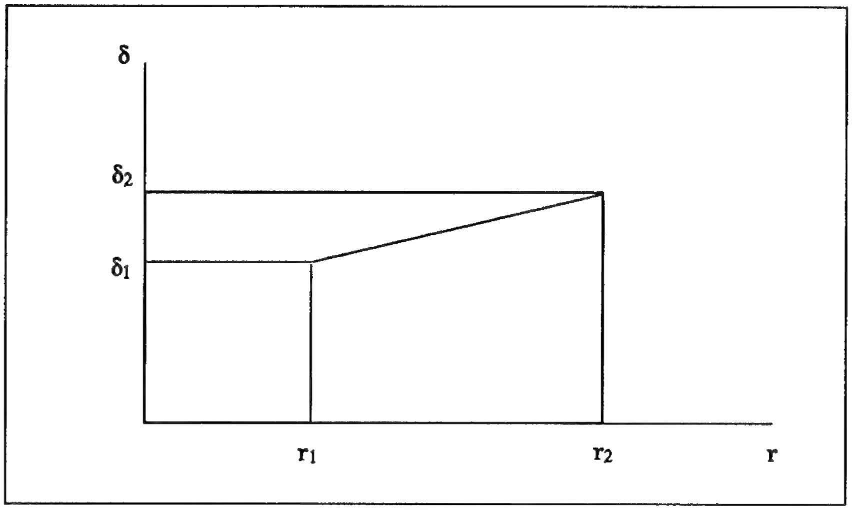

Figure 1

their data set derives largely from time-series and inter-occupational differences in reenlistment bonuses. Yet reenlistment bonuses may be endogenous, with low reenlistment rates leading the Army to compensate with higher bonuses. Hence their primary source of variation may engender a downward bias in the pay coefficient. Inclusion of dummy variables for MOS might mitigate some of this bias.

Other "experiments" may permit better identification of r. In earlier work, Cylke et al. (1982) computed the effect of reenlistment bonuses on reenlistment rates under two different payment schemes. One scheme paid the entire bonus as a lump-sum on the date of reenlistment. The other scheme spread the bonus into equal annual installments. Our pay variable was the *undiscounted* bonus amount. This variable had a greater effect on reenlistment rates under the lump-sum payment scheme, and we used the magnitude of this difference to infer a real discount rate of 18 to 20 percent for first-term Navy sailors. Although I fully endorse the use of alternative approaches for estimating the discount rate, the disparity between our results suggests that the issue remains unresolved.

Parameterization and Confidence Intervals

It is reasonable to require a positive estimate of r. To enforce this restriction, one could explicitly treat the estimation problem as a constrained nonlinear program. Alternatively, one could express the model in terms of an unrestricted parameter, and transform the estimate of that parameter into an estimate of r. The simplest choice is to define $r = \exp(\phi)$, or $\phi = \log(r)$. Any real value of ϕ implies a positive value of r. Moreover, the standard error of r may be obtained from the standard error of ϕ using a first-order Taylor series approximation.[2]

Daula and Moffitt use a different transformation. They first define the *discount factor* as $\beta = 1/(1+r)$, so the β is restricted to the interval (0,1). To obtain an unrestricted parameter, they define θ by

Hence: $$\beta = \left\{ [\tan^{-1}(\theta)] / (\pi/2) \right\}^2$$

$$r = T(\theta) = \left\{ [\tan^{-1}(\theta)] / (\pi/2) \right\}^{-2} - 1$$

This transformation is much more complicated than the exponential transformation that I suggest, and I do not see any advantage to their approach.

Construction of confidence intervals is closely related to model parameterization. Their maximum likelihood estimate is r = .03, with a standard error (by the delta-method) of .02. Strictly speaking, these values imply a symmetric confidence interval given by .03 plus/minus 2(.02), or [–.01, .07]. However, they truncate this interval to [.00, .07].

Symmetric confidence intervals may be undesirable, even apart from violation of domain restrictions. The likelihood profile[3] expresses the log-likelihood as a function of the single parameter r, when all other parameters are chosen to maximize the log-likelihood conditional on r: $L(r) = \mathrm{Max}_{\lambda} L(r,\lambda) = L[r,\lambda(r)]$, where L is the log-likelihood function and λ is the vector of parameters excluding r. Each column in Table 4 (Daula and Moffitt, 1989) gives one point on the likelihood profile. The entire likelihood profile may appear as in my Figure 2.

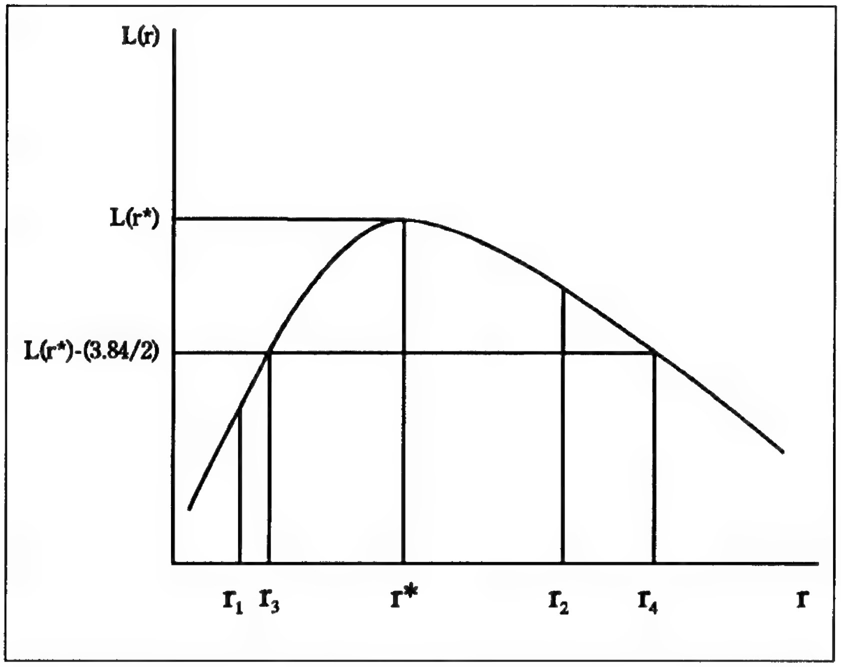

Figure 2

A symmetric confidence interval, even if restricted to the positive half of the axis, includes values of r that are not all equally likely. As I have drawn the figure, the left-hand endpoint, r_1, is much less likely than the right-hand endpoint, r_2. A better interval would be skewed to the right, thereby excluding values like r_1, but including more likely values to the right of r_2.

A skewed interval may be constructed using the asymptotic chi-squared distribution of the likelihood ratio statistic, $2\,[L(r^*) - L(r)]$. With the single parameter r and a 95 percent confidence level, it follows that

$$\begin{aligned} .95 &= \Pr\left\{ 2\,[\, L(r^*) - L(r)\,] \le 3.84 \right\} \\ &= \Pr\left\{ L(r) \ge L(r^*) - (3.84/2) \right\} \end{aligned}$$

The set of values {r} that satisfy this inequality forms a 95 percent confidence interval for r. This interval is depicted as $[r_3, r_4]$ in Figure 2. Note that r_3 must be positive because L(r) is undefined at negative arguments.

The likelihood profile requires a grid search over r, to find the values r_3 and r_4 where the log-likelihood drops by exactly (3.84/2) units. However, a much simpler alternative is available that also yields an asymmetric, positive interval. Recall that the model is estimated in terms of the unrestricted parameter θ. First form the symmetric interval θ^* plus/minus 1.96 $\mathrm{Var}^{1/2}(\theta^*)$, or $[\theta_1,\theta_2]$. Then observe that, because r is monotone increasing in θ

$$\begin{aligned} .95 &= \Pr\left\{\theta_1 \le \theta \le \theta_2\right\} \\ &= \Pr\left\{T(\theta_1) \le T(\theta) \le T(\theta_2)\right\} \\ &= \Pr\left\{T(\theta_1) \le r \le T(\theta_2)\right\} \end{aligned}$$

The interval $[T(\theta_1),T(\theta_2)]$ is generally asymmetric, and $T(\theta_1)$ is positive because the range of the function $T: \theta \to r$ is the positive half of the axis.[4]

Summary

In summary, I make the following three suggestions:

1. Introduce dummy variables for MOS to temper the endogeneity of the reenlistment bonus;

2. Check the correlation between the estimates of the discount rate and the pay coefficient to determine whether these parameters are separately identified; and

3. Compute an asymmetric confidence interval for r, using either the likelihood profile in r or an exact transformation of the symmetric confidence interval for θ.

Notes

1. Calculation of standard errors should not be prohibited in this class of models. An approximate Hessian matrix may be built up using only first-order (i.e., gradient) information, along the lines of Berndt et al. (1974) or Redner and Walker (1984). Yet another alternative is the bootstrap technique of Efron (1979).

2. Statisticians refer to this procedure as the "delta-method"; see Rao (1973) for an original source, or Goldberg and Follmann (1988) for a recent survey. Daula and Moffitt refer to this procedure as the "method of statistical differentials," but their terminology is not standard.

3. See Cox and Oakes (1984) or Goldberg and Follmann (1988).

4. As Thomas Daula has noted, the delta-method is just a first-order Taylor series approximation to the function T. Higher-order terms (e.g., a second-order expansion) yield a closer approximation, but even standard errors derived in that way should not be applied symmetrically to form confidence intervals. I prefer to use the *exact* function T, avoiding approximations entirely and yielding an asymmetric, positive confidence interval for r.

5

The Quality Dimension in Army Retention

Charles Brown

Studies of enlistment and of retention offer a striking contrast in the treatment of the "quality" of those who are enlisting and those who are contemplating reenlistment. The standard model of enlistment behavior (Fisher, 1969; DeVany and Saving, 1982; Dale and Gilroy, 1984; Brown, 1985; Horne, 1985; Ellwood and Wise, 1987) has the number of high-quality recruits as being driven by supply (the Army typically will take as many as wish to enlist), but the number of lower quality enlistees is rationed by the Army so that total enlistments are equal to enlistment targets.[1] The quality (measured by Armed Forces Qualification Test, or AFQT, scores and high school graduation) of enlistees has been a prominent and persistent part of the policy discussion about the continuing viability of the All-Volunteer Force.[2]

The quality issue deserves at least as much attention in reenlistment studies as in analyses of initial enlistment, for three reasons. First, the usual presumption is that the value of individuals to an organization is more sensitive to their quality the higher their position. Second, while the reluctance of the armed forces to pay very different wages to those with different levels of performance suggests attention to quality issues at all levels, this problem is to some extent finessed at the entry level by offering educational benefits that are dif-

ferentially attractive to those who have completed high school and have good test scores. But this would seem to create incentives for these very individuals to leave after completing their initial term of service. Third, the quality of those who reenlist remains a critical concern even for those who prefer to solve enlistment problems with a nonvolunteer force (draft, national service, etc.).

However, previous studies of reenlistment (or, more broadly, retention)[3] have paid too little attention to the quality of those who reenlist. The quality issue is shortchanged in two surprising ways. First, while quality indicators are often included as control variables in retention equations, the implications of those equations for the quality mix of those staying and leaving is not made clear. The typical study includes military and civilian pay as variables of central interest, and these values (especially civilian pay) are estimated based on the individual's quality indicators. With these (and other control variables that may have some correlation with the quality indicators) in the equation, the overall (i.e., not *ceteris paribus*) relationship between quality and retention is unclear. Second, quality continues to be measured by AFQT and high school graduation in most retention studies, even though the Army has observed (and to some extent conducted written evaluations of) actual performance.

Ward and Tan's (1985) analysis of the quality issue is probably the previous study that is closest in spirit to the analysis that follows. They model quality as a latent variable, determined in part by AFQT and schooling, and quality in turn determines speed of promotion (which they take to be their ultimate quality indicator). They find those with more schooling or higher AFQT scores are less likely to reenlist, but those with more of the unobserved quality (which, however, is related to observable promotion rates) are more likely to do so.

In contrast, this study treats education, AFQT, grade level, and scores on Army proficiency tests as quality indicators, thus putting less emphasis on promotion as the ultimate indicator of quality. One motivation for doing so is the fact that the Army has changed its "formula" for promotions, in part because of a recognition that it provided too many "promotion points" to attributes with too weak a relationship to performance. Thus,

using promotion as the ultimate quality indicator is too restrictive. Second, this study attempts to explicitly model the determinants of being ineligible to reenlist, among those who have completed their term of service. Since restricting eligibility is an alternative to performance-based pay in raising the average quality of those who reenlist, explicit consideration of ineligibility is warranted.

I. A Model of Wage Structure and Worker Quality

In order to understand how various features of the Army's personnel system affect the quality of those who reenlist, it is useful to construct a simple model of the reenlistment decision. Individuals differ in a variety of attributes, X, which influence their reenlistment decision and also contribute to (or detract from) their value to the Army. Concretely, X would include often-emphasized factors such as a high school diploma and one's score on the AFQT; one can imagine many other potential Xs as well.

Differences in X generate different retention outcomes in three ways: by influencing the level of military compensation one can expect, by influencing potential civilian compensation, and perhaps by affecting the way in which one evaluates the nonpecuniary features of military and civilian life. A simple statistical model of this decision can be based on the idea that each individual has an index R of the *net* advantages of remaining in the military, which depends on X and on unmeasured factors e:

(1) $$R = XB + e$$

and an individual reenlists if this index is sufficiently high. We can arbitrarily set the critical value of R, which divides those who wish to reenlist from those who do not at zero, and so

(2) $$\text{reenlist if } R > 0.$$

Because the reenlistment decision is a choice between alternatives, it is the effect of X on the *net* advantages of remaining in the military that is central to equations (1) and (2). If, as evidence in Section III suggests, Army pay is less sensitive than civilian pay to differences in education or test scores, then the effects of education or test scores on reten-

tion will be negative—unless these differences are offset by differences in the evaluation of nonpecuniary characteristics of military and civilian life. Thus, the model does not *predict* that those who reenlist will have fewer desirable Xs than those who leave at the expiration of their term of service (ETS), but it does *suggest* that this is an interesting and potentially troubling hypothesis to investigate. In order to do so, we must model the quality of those who reenlist (and those who don't) more carefully. Many of the factors one might think of as natural empirical components of X, such as high school diploma or AFQT scores, are also quite likely to be determinants of the individual's "quality" (or value to the organization) if he/she reenlists; it is hard to think of factors that would influence retention one would be confident could not be determinants of "quality," or vice versa. Hence, an obvious statistical model for quality is

$$Q = XA + u \tag{3}$$

where Q is quality as seen by the Army and u is uncorrelated with X. If the Army accepted anyone who wished to reenlist, the average quality of those who did so would be $E(Q \mid R>0)$. Both Roy's (1951) classic paper on workers' choice of occupation and much recent work (e.g., Heckman and Sedlacek, 1985, on wages and business cycles, and Borjas, 1987, on earnings of immigrants) use this statistical model.

While the decision to reenlist is voluntary in the sense that individuals are free to opt out, it is not made unilaterally by the individual. The Army can (and does) exclude from reenlisting a nontrivial fraction of those who reach ETS. A natural way to model this component of the problem is to assume that only those who achieve a certain level of quality are eligible to reenlist, and so

$$\text{reenlist if } R > 0 \text{ and } Q > 0. \tag{2a}$$

In (2a), quality is "measured" so that Q=0 is the threshold level of quality for eligibility to reenlist. Equations (1) and (3) and condition (2a) are the basis for the empirical work done in Section IV.

The main substantive conclusion of the theoretical model is that a pay-quality relationship which is less pronounced than

that in the civilian sector raises the danger that those retained will be those with relatively low ability and proficiency in their tasks. But there are two ways of avoiding this "brain drain" to the civilian sector. First, the best soldiers may have a positive preference for the military, either because doing their work well makes the work more attractive or because their superiors arrange the nonpecuniary aspects of military life to their advantage. The good-workers-are-happy-workers possibility seems to be most promising in those fields (e.g., infantry) with few civilian analogues. Second, the military may make staying sufficiently attractive that significantly more will want to reenlist than are needed; it can then select rather than simply accept the soldiers' self-selection decisions.

II. Data

The data for this paper are drawn from the ARI Enlisted Panel Research Data Base (EPRDB). The compilation of this data base began with a 25 percent sample of all enlisted accessions in the U.S. Army during fiscal years 1974–1984. The Enlisted Accession File contains information about the individual as of his/her entry into the Army (e.g., schooling, AFQT score, initial assignment). For each individual in the 25 percent sample, Master/Loss files were searched in subsequent years, and the last such record in each fiscal year for that individual was retained. The Master/Loss file, as its name implies, contains information on separations from the Army; it also includes information on reenlistment and other extensions of the service contract. Similarly, the Army Enlisted Master File was also searched, and Personnel Command's records for fiscal years 1984–87 for those in the sample were also retained. For our purposes, a critical further source of data is the 1980–86 file of scores on the Skill Qualification Test (SQT), which characterizes the individual's proficiency in his/her occupational specialty after completing training (and periodically thereafter).

The file described so far contained information for over 450,000 individuals. In order to keep the project to a manageable scope, it was decided to restrict the analysis to those in three Career Management Fields (CMFs): Infantry, Mechanical Maintenance, and Administration. (The latter group

should be thought of as including office support staff rather than top decision makers.) In addition, I focused on those deciding on a first reenlistment during fiscal years 1985–87. The decision to focus on these more recent cohorts was based on the fact that, while SQTs became operational in fiscal year 1977, as late as fiscal year 1984 a significant fraction of the enlisted force had no SQT score in their files (Grafton and Horne, 1985, pp. 2-3). Since the most common term of enlistment is three years, this means our analysis is restricted to those whose initial enlistments occurred after the large increases in military pay in 1980–81 and who had much better test scores and high school graduation rates than those in cohorts entering a few years earlier.

The first and most complicated step in describing individual variables is to explain how reenlistment and eligibility to reenlist were defined. When an individual enlists initially, it is for a definite term of service (most often three or four years). An eligible individual may decide to reenlist starting at the expiration of the previous commitment, or in some cases shortly before. However, for a variety of reasons an individual may also "extend" this commitment for a shorter (typically less than two-year) period. Extensions require either a considerable complication of the analysis (if treated as a separate outcome) or an essentially arbitrary decision to ignore them. Following most research on the topic, I have done the latter—if an individual with a three-year initial commitment extended for one year, it is treated as if the individual's initial commitment had been four years (and hadn't been extended).

Because our focus is on the decision to reenlist, we focus on those who reach the reenlistment decision—i.e., who remain in the Army until (near) the end of their initial commitment. Specifically, those who leave more than six months prior to completing their initial commitment are excluded from the analysis. Thus, the focus is on reenlistment conditional on completing the first term of service (and any extensions), not the unconditional reenlistment rate. Warner and Solon (1989) find little evidence of selectivity bias in estimating first-term reenlistment equations in their sample from the EPRDB (1974–83 Infantry enlistees), though they caution that this finding need not hold as a general rule.

Most but not all of those who leave the Army after completing their first term of service could have reenlisted had they chosen to do so. We count as "ineligible" those who are disqualified from reenlisting due to either a waivable or a nonwaivable disqualification. Both the Army's "Reenlistment Eligibility" codes and the "Interservice Separation Code" were scanned for evidence of such disqualifications.

One complication of judging eligibility is that it may not be determined independently of the individual's decision to reenlist. Some reenlistment bars arise because of action taken by one's commanding officer and, because they require considerable effort, may not be imposed on an individual who clearly intends not to reenlist. On the other hand, individuals with bars to reenlistment may succeed in getting them removed if they are serious enough about reenlisting. Thus, in terms of the model in Section I, the threshold of performance below which one is deemed ineligible in these data may be different for those with R>0 than for those with R, and the difference may be either positive or negative. This issue is addressed in the empirical work in Section V.

We have three types of individual attributes whose impact on reenlistment and eligibility are investigated. The first is high school graduation, which is represented by dummy variables for graduates and those who received a GED (general educational development high-school equivalence); the omitted group is those who neither graduated nor obtained a GED. AFQT scores are measured in percentile terms, using renormed test scores introduced in 1984. Both high school graduation status and AFQT are measured at time of entry into the Army, rather than at the time the reenlistment decision is being made.

Our SQT measure was obtained by starting with the SQT score for the year in which the reenlistment decision is being made and going to earlier years as necessary, to find a score for each individual. However, mean SQT scores vary widely from one Military Occupational Specialty (MOS, or detailed occupation) to the next, in a way seemingly unrelated to the technical complexity of the MOS, and from year to year. Moreover, one is tested at a different "level" depending on one's pay grade (SQT level=grade 3, but with level 1 applying to pay grades E4

and lower). Therefore, a standardized SQT score was computed, subtracting the mean and dividing by the standard deviation of scores in the relevant MOS-level-year cell. Once these noncomparabilities across level, MOS, and year have been overcome, "there is little disagreement that the scores of soldiers taking a specific SQT accurately reflect differences in performance" (Grafton and Horne, 1985, p. 3). In addition to this normalized score, the level of the SQT was also included; it measures how fast the individual has been promoted as well as the level of the SQT test.

III. Military and Civilian Pay

It seems relatively well established that the military is, in fact, an "egalitarian" institution in that the pay structure is relatively compressed once length-of-service increments are factored out of the pay data (see, e.g., Baldwin and Daula, 1985b, p. 354). Given lack of micro data on earnings of those who leave the military and the obvious sample selection issues, it is difficult to quantify this difference in pay structures. Nevertheless, Smith, Sylwester, and Villa (1989)—hereafter SSV—provide a good indication of the sensitivity of military and civilian pay to individual characteristics.

For those in the EPRDB who reach a reenlistment decision, SSV estimated the present value of civilian earnings if they do not reenlist and the present value of military compensation plus later civilian earnings if they decide to reenlist. The present value of the military-then-civilian sequence depends on how long one remains after reenlisting; SSV use the horizon H which would maximize the annualized value of this option (generally, staying until retirement at 20 years of service). The civilian compensation estimate is based on grouped earnings data for previous cohorts of separatees; the military compensation estimate combines information on military pay by grade and years of service, estimated promotion rates, reenlistment bonuses, pensions, and civilian earnings after leaving the military. SSV then calculate the annualized cost of leaving, ACOL, which is equal to the present value of reenlisting and staying H more years minus the present value of civilian earnings if one does not reenlist, annualized over the horizon H.

In addition to the careful treatment of the complex military pay system, SSV's tabulations have a second important feature: they are presented separately for (infantry) enlistees with different AFQT scores and education levels. ACOL is \$775 (1980 dollars) larger for those with below-average AFQTs than for those with above-average scores, and \$1700 larger for high school dropouts than for those with education beyond high school. Indeed, this pattern persists even if one uses Army promotions as the indicator of quality—the civilian sector pays a higher premium to those who have been more rapidly promoted than does the Army. (The difference in ACOL between those with below-average promotion records and average or better records is \$1000.) SSV conclude, as did Baldwin and Daula, that "across all these indicators of employee performance,... relative military-civilian compensation is lower for good performers."

IV. Simple Tabulations

The tendency for military pay to be less sensitive to observable indicators of enlistee quality than civilian pay suggests that retention of the best enlisted personnel may be difficult. Tables 5.1–5.3 contain simple tabulations that address this concern.

In each table, three possible outcomes are identified: reenlistment, normal separation (i.e., separation at ETS date with no bar to reenlistment), and ineligible separation (i.e., separation at ETS but ineligible to reenlist). For those with particular levels of a quality indicator (e.g., AFQT scores in the lowest 30 percentiles), the probability of each outcome conditional on (at least nearly) reaching ETS is indicated.

Results for Infantry are presented in Table 5.1. The first panel gives fairly dramatic reinforcement to the concern about the quality of those who reenlist. Reenlistment is lower for those with higher AFQT scores. Ineligibility to reenlist is also lower among those with good AFQT scores.

The second panel presents a similar tabulation, but with high school graduation as the quality indicator. The main result here is that high school graduates are more likely to be eligible to reenlist, but no more likely to do so. Perhaps surprisingly, those with GED high-school equivalences do not exhibit

Table 5.1
Outcomes by Enlistee Characteristics
Infantry, 1985–87

	Percent Probability of			
Characteristic	**Reenl**	**NSep**	**Inel**	**Number of Cases**
AFQT 1–30	35	49	17	1904
AFQT 31–49	33	54	14	2215
AFQT 50–64	28	57	15	1234
AFQT 65+	24	65	11	2267
Education < HS Grad	30	47	23	544
Education = GED	24	52	24	183
Education = HS Grad	30	57	13	6900
SQT < –.5	28	52	20	1593
SQT –.5 to .5	30	56	14	2871
SQT >.5	32	59	9	2319
SQT Level = 1	28	57	15	6198
SQT Level > 1	52	45	3	599
SQT Level Missing	27	59	14	830

behavior between those with a diploma and those with no high-school credential: GEDs are less likely to reenlist (and less likely to be eligible) than are other groups.

The third panel presents retention outcomes for those with differing SQT scores. While the differences between SQT-score groups are not enormous—neither enlistee decisions nor Army eligibility decisions are deterministic functions of SQT—they suggest that those with higher SQT scores are more likely to reenlist, and less likely to be ineligible to stay beyond their first term. The fourth panel is consistent with this view: those who take the SQT at a higher level (i.e., have reached a higher pay grade) are likely to remain. This is not surprising, but it was not predictable either: civilian earnings of those who are promoted faster are also higher than those who are less quickly promoted while in the military. The final line of the table shows the proportion of the sample with missing SQT level (and missing SQT scores).[4] While these account for about 10 percent of the overall sample, the proportion missing does not vary a great deal across outcomes.

Similar tabulations for those making reenlistment decisions in 1982–84 are presented in Appendix Table A-1. The sample proportions for the various quality indicators are quite different (proportionally fewer high school graduates and high AFQT scores). However, for a given quality indicator, the patterns of retention outcomes are broadly similar, the main difference being evidence of higher reenlistment rates for high school graduates.

Results for Mechanical Maintenance are presented in Table 5.2. The results are broadly similar to those for Infantry, with some differences on subtler points. Those with higher AFQT scores are again less likely to reenlist or to be ineligible. High school graduates are somewhat more likely to reenlist, and again more likely to be eligible to do so. The same holds for those with high SQT scores, and in higher grades who take the higher level SQTs. Missing SQT data is somewhat more common here than in Table 5.1, and those with missing SQTs are less likely to reenlist (by about 5 percentage points).

Similar tabulations for those in Mechanical Maintenance facing reenlistment decisions in 1982–84 are presented in Appendix Table A-2. Again the broad patterns of the later data can be seen here, too. The unavailability of SQT scores is much more striking here than in the Infantry results for the same years in Appendix Table A-1.

Table 5.2
Outcomes by Enlistee Characteristics
Mechanical Maintenance, 1985–87

	Percent Probability of			
Characteristic	**Reenl**	**NSep**	**Inel**	**Number of Cases**
AFQT 1–30	38	46	16	1859
AFQT 31–49	34	53	13	2194
AFQT 50–64	31	55	14	926
AFQT 65+	31	57	12	987
Education < HS Grad	32	45	23	597
Education = GED	37	43	20	203
Education = HS Grad	35	53	13	5175
SQT < –.5	30	51	19	1261
SQT –.5 to .5	37	50	13	2073
SQT > .5	37	52	11	1691
SQT Level = 1	34	52	14	4774
SQT > 1	59	34	7	259
SQT Level Missing	30	55	15	943

Outcomes for those in Administration appear in Table 5.3. Those with higher AFQT scores are again less likely to reenlist and more likely to be eligible to do so. High school graduates are more likely to be eligible to reenlist but *less* likely to do so.

Table 5.3
Outcomes by Enlistee Characteristics
Administration, 1985–87

	Percent Probability of			
Characteristic	**Reenl**	**NSep**	**Inel**	**Number of Cases**
AFQT 1–30	53	32	15	530
AFQT 31–49	47	42	12	733
AFQT 50–64	40	53	8	367
AFQT 65+	32	59	9	775
Education < HS Grad	56	24	20	121
Education = GED	47	37	16	38
Education = HS Grad	41	48	10	2248
SQT < –.5	42	42	16	644
SQT –.5 to .5	44	47	10	722
SQT > .5	47	46	7	701
SQT Level = 1	42	47	11	1916
SQT > 1	68	29	2	163
SQT Level Missing	31	58	11	328

Those with higher SQT scores and SQT level are again more likely to reenlist and to be eligible. About 15 percent have missing SQTs, and there is a clearer tendency for these to be those who do not reenlist. Similar patterns (but with no effect of high school graduation on reenlistment) are evident in the tabulations for 1982–84 decisions, in Appendix Table A-3.

V. A More Formal Analysis

The model presented in Section I was based on two equations, one governing the enlistee's desire to reenlist and the other representing the Army's willingness to let him do so. That model would treat the probability of reenlistment as Prob($R>0,Q>0$), the probability of a normal separation as Prob($R<0, Q>0$), and the probability of an "ineligible" separation as Prob($Q<0$). However, as noted in Section II, the threshold for eligibility to reenlist could be either higher or lower than that for those who have no such desire. Consequently, define θ as the threshold for reenlistment eligibility for those not desiring to do so. Then the probability of reenlisting is again Prob($R>0,Q>0$) but the probability of normal separation is Prob($R<0,Q>\theta$) and one minus the sum of these two probabilities is the probability of an ineligible separation.

In obtaining the estimates of B and A, it was assumed that e and u came from a bivariate normal distribution, each having mean zero and variance one, and a correlation between them of ρ. Normality is neither obvious nor innocuous, but alternative distributions with nonzero correlation between e and u are much more difficult to implement. Since ρ (and, to some extent, θ) are identified by functional form assumptions rather than "real stuff," and because obtaining convergence with all parameters free proved elusive (not an uncommon problem in such models), estimates are presented for $\theta=\rho=0$, and for combinations of θ from -1 to $+1$ and ρ from $-.5$ to $.5$. The first combination ($\theta=\rho=0$) is a sensible place to start given that there is no particularly strong presumption about the sign of either θ or ρ.

The estimation was done using the GQOPT nonlinear optimization routine (Quandt and Goldfeld, 1984). The standard errors were calculated using the BHHH method (Berndt, Hall, Hall, and Hausman, 1974); these were checked against those obtained from inverting the matrix of second-partial derivatives of the log-likelihood function (and there were no noteworthy discrepancies).

Estimates for those in the Infantry, conditional on both θ and ρ being zero, are presented in the top panel of Table 5.4. The first column contains the estimates of the determinants of R, the latent variable that governs the individual's willingness

Table 5.4
Reenlistment Model for Infantry

Explanatory Variable	Coefficients in Equation for R	Coefficients in Equation for Q	Derivative of Probability of[a] Reenl	Derivative of Probability of[a] NSep
θ=0, ρ=0, LLF=−6295.12				
Constant	.228 (2.81)	.640 (7.66)		
HS Graduate	−.202 (2.86)	.388 (5.69)	−.034	.122
GED	−.127 (.93)	−.021 (.16)	−.040	.035
AFQT Score	−.983 (11.9)	.134 (1.41)	−.286	.316
SQT Score	.104 (5.10)	.175 (8.24)	.043	−.004
SQT Level	.620 (10.83)	.757 (7.35)	.239	−.067
θ=−1, ρ=−.5, LLF=−6294.47				
Constant	.521 (7.20)	.562 (5.86)		
HS Graduate	−.311 (5.03)	.388 (4.96)	−.033	.124
GED	−.086 (.73)	−.029 (.20)	−.031	.032
AFQT Score	−.862 (11.41)	−.130 (1.18)	−.287	.324
SQT Score	.023 (1.27)	.227 (9.20)	.044	−.005
SQT Level	.419 (7.50)	.938 (8.62)	.282	−.143

[a]Sample probabilities: Reenlist, .302; Normal separation, .558; Ineligible = .140. N = 6790.

t-ratios appear in parentheses below coefficients.

to reenlist. Those with higher AFQT scores and those with high school diplomas are less likely to desire to reenlist, while those with higher SQT scores and those whose SQT tests are

at a higher level (i.e., those who have been promoted in the past) are more likely to do so. The second column presents the relationship between these same variables and Q, the latent variable governing eligibility to reenlist. Those with diplomas, good SQT scores, and higher SQT levels are more likely to be eligible to reenlist; those with higher AFQT scores are more likely to be eligible, too, but this link is not statistically significant.

Interpreting these two columns of coefficients is complicated by the fact that the model relates observables to latent variables, while our sense of importance of effects depends on their impact on observable probabilities. Therefore, the effect of the variables on the probability of reenlisting (Prob $R>0,Q>0$) is presented in column 3, while the effect on probability of normal separation (Prob$R<0,Q>\theta$) is presented in the final column. The sum of these two represents the effect on the probability of being eligible to reenlist. One can think of these as multivariate versions of the simple tabulations in Section IV.

The effect of high school graduation on the probability of reenlisting is small, while its effect on the probability of normal separations is greater: the implied reduction in the probability of being barred from reenlisting (.088) is large given that only 14 percent of the sample is ineligible. Those with GEDs are less likely to reenlist and more likely have normal separations; these effects are statistically fragile and so they should be given little weight. The negative effect of AFQTs on reenlistment is paired with a near-equal increase in normal separations, the implied effects on eligibility being small. Higher SQTs and SQT level increase the probability of reenlistment, with a similarly sized increase in eligibility. Finally, while the standard deviation of SQT is by construction 1.0, one standard deviation of AFQT score is .23 (AFQT being uniform on (0,1) in the population). Therefore, a one-standard-deviation increase in AFQT reduces the probability of reenlistment by about .067, while a one-standard-deviation increase in SQT raises it by .043.

While the other θ, ρ combinations produced log-likelihoods which were not very different from that for $\theta=\rho=0$, and so there is no strong basis for preferring alternative values, the combination preferred by the likelihood function was $\theta=-1$, $\rho=-.5$. Estimates of the other parameters of the model conditional on these values are presented in the bottom panel of Table 5.4. The most

important difference between the two panels is that SQT scores have a smaller and statistically more fragile impact on desire to reenlist. Nevertheless, it remains true that those with higher SQT scores are more likely to reenlist by a practically important margin.

Parameter estimates conditional on other values of θ and ρ are presented in Appendix Table A-4. There are few surprises. The negative impact of high school graduation on desire to reenlist varies quite a bit with the assumed values of θ and ρ, while the impact of SQT scores is consistently positive. The impact of AFQT on Q proves quite sensitive to choice of θ and ρ. Comparing the derivatives of the reenlistment and normal separation probabilities shows an impressive consistency: it is partitioning these derivatives into effects on R and Q that is more sensitive to θ and ρ.

The SQT score used in both Table 5.4 and Appendix Table A-4 was chosen by starting with the decision year and working backward to earlier years if necessary. This gives the last (through the decision year) available SQT score, a choice which might be challenged on two grounds. First, those who decide to reenlist might be more likely to "cram" for the SQT, in effect overstating their day-to-day performance. Second, it is possible the SQT score we have comes from a test taken *after* the reenlistment decision.

To see whether these concerns could be very important, the analysis was redone using the second-to-last SQT (from a year before the decision) instead of the latest whenever more than one was available. The effects of SQT scores on R were about three-quarters as large as in Table 5.4 and Appendix Table A-4, with a similar pattern of statistical significance. However, the $\theta=-1$, $\rho=-.5$ pair was the one least preferred by the data, and for the remaining pairs the t-ratio for the SQT score was 3.2 or higher.

Estimates for those in Mechanical Maintenance are presented in Table 5.5. Probably the most striking result is the similarity to those in Table 5.4. In Table 5.5, high school graduation has a much weaker (negative) impact on desire to reenlist, though the positive impact on eligibility to do so remains strong. GED effects are again statistically very weak. Those with higher AFQT scores are again much less likely to reenlist than those with lower scores; this impact is only about three-quarters as large as it was for those in Infantry. Those with higher SQT

Table 5.5
Reenlistment Model for Mechanical Maintenance

Explanatory Variable	Coefficients in Equation for R	Coefficients in Equation for Q	Derivative of Probability of[a] Reenl	Derivative of Probability of[a] NSep
θ=0, ρ=0, LLF=–4830.98				
Constant	.075	.537		
	(.93)	(6.35)		
HS Graduate	–.071	.482	.015	.082
	1.06)	(7.17)		
GED	.159	.175	.069	–.033
	(1.24)	(1.30)		
AFQT Score	–.703	.307	–.214	.276
	(6.72)	(2.48)		
SQT Score	.099	.135	.045	–.017
	(4.47)	(5.81)		
SQT Level	.600	.454	.241	–.149
	(7.00)	(3.65)		
θ=–1, ρ=–.5, LLF=–4828.90				
Constant	.419	.406		
	(5.75)	(4.25)		
HS Graduate	–.223	.521	.009	.091
	(3.73)	(6.85)		
GED	.073	.249	.067	–.027
	(.63)	(1.66)		
AFQT Score	–.689	.156	–.214	.272
	(7.09)	(1.12)		
SQT Score	.040	.186	.045	–.014
	(2.02)	(7.01)		
SQT Level	.455	.585	.255	–.175
	(5.44)	(4.56)		

[a]Sample probabilities: Reenlist, .351; Normal separation, .512; Ineligible = .137. N = 5023.
t-ratios appear in parentheses below coefficients.

scores are again more likely to reenlist, though the impact of SQT scores on desire to reenlist is barely significant statistically when $\theta=-1$ and $\rho=-.5$. SQT level is again associated with greater probabilities of wanting to reenlist and being eligible to do so.

Results for other θ,ρ combinations appear in Appendix Table A-5. It is also quite similar to the corresponding table for those in the Infantry: the effects of high school graduation on desire to reenlist and of AFQT on eligibility to do so are again sensitive to the choice of those parameters. Using second-to-last SQT scores reduced the SQT impacts on R by about a third, and essentially eliminated it for the preferred $\theta=-1$, $\rho=-.5$ parameter set.

Finally, results for those in Administration are presented in Table 5.6. Again, the similarity of these results to those for the other CMFs is striking. The relationships between quality indicators and desire to reenlist (negative for high school graduation, strongly negative for AFQT, positive for SQT score and level) from earlier tables reappear. Indeed, the positive effect of SQT scores is now statistically virile even for $\theta=-1$ and $\rho=-.5$. High school graduation and SQT scores and level are positively related to quality; the weakness of AFQT in the equation for Q also persists.

The combined effects of the Bs and As on the probabilities of reenlisting and being eligible to do so are also similar to those in earlier tables. High school graduation has a huge effect on being eligible to reenlist (derivative=.116, versus sample mean ineligibility rate of .107). AFQT's negative effect on reenlistment is matched by a larger increase in normal separations; the positive effect of SQT scores and level on reenlistment comes from both fewer normal separations and less probability of being ineligible to reenlist.

In general, these patterns are even less sensitive to choice of θ and ρ than for Infantry or Mechanical Maintenance (see bottom panel of Table 5.6, and Appendix Table A-6). Substitution of next-to-last SQT scores when possible reduced the SQT's effect on R by about one-quarter, but the smaller coefficients were uniformly significant statistically.

The model in Section I identified two determinants of the quality of those who reenlist—the extent to which net ad-

Table 5.6
Reenlistment Model for Administration

Explanatory Variable	Coefficients in Equation for R	Coefficients in Equation for Q	Derivative of Probability of[a] Reenl	Derivative of Probability of[a] NSep
θ=0, ρ=0, LLF=–1895.01				
Constant	1.182 (7.49)	.645 (3.80)		
HS Graduate	–.502 (3.49)	.438 (2.96)	–.041	.157
GED	–.346 (1.29)	.169 (.55)	–.055	.100
AFQT Score	–1.490 (10.11)	.343 (1.81)	–.313	.404
SQT Score	.167 (5.07)	.107 (2.85)	.064	–.036
SQT Level	.633 (5.55)	.741 (3.57)	.311	–.114
θ=–1, ρ=–.5, LLF=–1894.96				
Constant	1.351 (9.14)	.697 (3.86)		
HS Graduate	–.564 (4.22)	.400 (2.54)	–.046	.157
GED	–.360 (1.43)	.165 (.50)	–.052	.100
AFQT Score	–1.420 (10.18)	.104 (.50)	–.343	.394
SQT Score	.123 (4.01)	.144 (3.51)	.068	–.034
SQT Level	.507 (4.51)	.826 (3.91)	.339	–.140

[a]Sample probabilities: Reenlist, .440; Normal separation, .453; Ineligible = .107. N = 2077.
t-ratios appear in parentheses below coefficients.

vantages of reenlisting are correlated with the quality indicators, and the extent to which eligibility bars prevent those

with low quality but high eagerness to reenlist from doing so. With the exception of AFQT, the quality indicators consistently show the expected positive effect on eligibility, but with ineligibility rates of only 11 to 14 percent one would expect the impact of eligibility bars to be fairly modest. That expectation is confirmed in Table 5.7, where mean values of the quality indicators for those who reenlist are compared to means simu-

Table 5.7
Impact of Eliminating Ineligibility on Means of Quality Indicators

CMF	Variable	Mean	
		Actual	No Ineligibility[a]
Infantry	HS Grad	0.907	0.889
	GED	0.020	0.026
	AFQT	0.475	0.473
	SQT	0.113	0.003
	SQT Level	0.152	0.112
Mechanical Maintenance	HS Grad	0.870	0.848
	GED	0.034	0.035
	AFQT	0.407	0.405
	SQT	0.156	0.076
	SQT Level	0.084	0.068
Administration	HS Grad	0.910	0.904
	GED	0.019	0.019
	AFQT	0.473	0.471
	SQT	0.013	−0.053
	SQT Level	0.120	0.101

[a]All "No ineligibility" simulations based on $\theta=-1$, $\rho=-.5$, which fit the data slightly better than other values.

lated on the assumption that all those who want to reenlist ($R>0$) are allowed to do so. While the difference in SQT level for Infantry is of perhaps moderately important magnitude, the remaining differences are small. (The large proportionate change in SQT is misleading: because our SQT variable is normed to have mean zero and standard deviation of one, the SQT changes are 10 percent of a standard deviation for Infantry and smaller for the two other CMFs.)

VI. Conclusions

Organizations like the Army with relatively "egalitarian" pay structures offer lower relative pay to those with the best civilian earnings alternatives, and higher relative pay to those with weaker civilian options. Assuming some commonality in the attributes that are valued by civilian employers and by the military, this suggests the possibility of difficulty in retaining those the Army would most wish to keep. If relative pay considerations make the Army less attractive for its best enlistees, there are two ways to avoid losing them. First, nonpecuniary factors might make reenlisting particularly attractive for high-quality enlistees—because success in the Army makes staying more rewarding (apart from dollar rewards), or because those who find the Army most attractive end up doing the best job, or because superior enlistees' commanding officers find ways to make the option of reenlisting attractive. Second, the Army may have more individuals willing to reenlist than it needs and be able to select the best from among those who would like to reenlist.

The evidence presented in this paper suggests that there is a significant tendency for those with high AFQT scores to decide not to reenlist. Reenlistment patterns of high school graduates and nongraduates were less clear-cut: graduates are more likely to be eligible to reenlist, but they were generally (i.e., in Infantry and Administration but not Mechanical Maintenance) less likely to do so.

If one judges "quality" by SQT scores, or the level of the SQT taken (which depends on grade level and hence prior promotions), the quality of those who reenlist looks a good deal better. Those with higher SQT scores are consistently more likely to be eligible to reenlist (which is hardly surprising), but

also generally more likely to want to do so. The same is true for SQT level.

A plausible conjecture is that the pecuniary and nonpecuniary rewards of a job well done are more likely to trigger reenlistment if "the job" cannot be performed in the civilian sector. If one enjoys doing Administration because one does it well, one can do this in either the military or the civilian market, and so the nonpecuniary factors would contribute little to retention. If one derives satisfaction from superior performance in Infantry occupations, however, there may be few civilian opportunities to use these skills. But in fact there was little evidence that successful performance encouraged reenlistment in Infantry more than it did in Mechanical Maintenance and Administration. Thus, the reason for the association between better SQT performance and reenlistment deserves further investigation.

Finally, using a relatively broad measure of ineligibility, only 11 to 14 percent of those reaching ETS are ineligible to reenlist. While those excluded are less likely to be high school graduates or have a high SQT score or level, their exclusion raises the average quality indicators of those reenlisting by quite small amounts. The similarity of the effects of SQT scores on retention across Career Managements Fields, noted above, is only an example of a more general robustness of the findings across fields. The main findings were also fairly insensitive to variations in the values assumed for hard-to-identify parameters of the formal model in Section V. The simple tabular results showed similar patterns for both 1982–84 and 1985–87 decisions, despite the lower scores on traditional quality indicators for the former group. Overall, one does see the robustness one hopes to be able to see at the end of an empirical undertaking of this sort.

Acknowledgments

I am grateful to participants at a conference sponsored by the U.S. Army Research Institute for comments on an earlier draft of this paper. D. Alton Smith and Stephen Sylwester provided a great deal of help with the intricacies of the data, and Thomas Hungerford and Marsha Silverberg handled the computer work with patience and skill.

Notes

1. Daula and Smith (1986) suggest that even high-quality enlistments reflect demand as well as supply forces.

2. See, e.g., Slackman's 1986 study for the Congressional Budget Office, whose title ("Quality Soldiers: Costs of Manning the Active Army") highlights this concern.

3. "Attrition" refers to failure to complete the term of service to which one originally committed; "extension" refers to a (typically) short period of remaining in the Army beyond one's term of enlistment without agreeing to a longer (typically three- to four-year) term of further service. "Retention" can include reenlistment, extension, or simply non-attrition.

4. Because few cases had missing information about high school or AFQT, these frequencies are not shown in the table.

Appendix Table A-1
Outcomes by Enlistee Characteristics
Infantry, 1982–84

	Percent Probability of			
Characteristic	**Reenl**	**NSep**	**Inel**	**Number of Cases**
AFQT 1–30	32	40	28	3861
AFQT 31–49	31	40	29	1746
AFQT 50–64	29	47	24	770
AFQT 65+	28	56	17	1207
Education < HS Grad	27	37	36	2834
Education = GED	31	42	27	248
Education = HS Grad	33	47	20	4508
SQT < –.5	29	40	31	1566
SQT –.5 to .5	33	41	26	2866
SQT >.5	35	44	21	2176
SQT Level = 1	27	44	29	5823
SQT Level > 1	66	30	4	879
SQT Level Missing	18	51	30	888

Appendix Table A-2
Outcomes by Enlistee Characteristics
Mechanical Maintenance 1982–84

Characteristic	Percent Probability of Reenl	NSep	Inel	Number of Cases
AFQT 1–30	34	43	23	3092
AFQT 31–49	28	47	25	1387
AFQT 50–64	27	52	20	600
AFQT 65+	28	51	20	635
Education < HS Grad	27	42	31	1794
Education = GED	28	40	32	202
Education = HS Grad	33	48	19	3727
SQT < –.5	32	43	25	635
SQT –.5 to .5	36	42	22	874
SQT >.5	39	45	16	647
SQT Level = 1	29	46	25	1853
SQT Level > 1	71	26	2	353
SQT Level Missing	28	48	44	3519

Appendix Table A-3
Outcomes by Enlistee Characteristics
Administration, 1982–84

	Percent Probability of			
Characteristic	**Reenl**	**NSep**	**Inel**	**Number of Cases**
AFQT 1–30	52	31	18	621
AFQT 31–49	47	35	18	515
AFQT 50–64	43	38	19	284
AFQT 65+	31	58	11	529
Education < HS Grad	42	28	30	306
Education = GED	54	19	26	68
Education = HS Grad	44	43	13	1579
SQT < –.5	37	45	17	398
SQT –.5 to .5	49	36	15	637
SQT >.5	49	41	11	557
SQT Level = 1	42	42	16	1357
SQT Level > 1	66	28	6	264
SQT Level Missing	31	43	26	332

Appendix Table A-4
Reenlistment Model for Infantry

Explanatory Variable	Coefficients in Equation for		Derivative of Probability of	
	R	Q	Reenl	NSep
	θ=1, ρ=.5, LLF–6296.14			
Constant	–.058	1.527		
	(.77)	(17.35)		
HS Graduate	–.090	.419	–.028	.117
	(1.38)	(5.82)		
GED	–.117	–.017	–.038	.032
	(.93)	(.13)		
AFQT Score	–.899	.216	–.290	.320
	(11.38)	(2.18)		
SQT Score	.137	.170	.045	–.005
	(7.12)	(7.76)		
SQT Level	.699	.708	.227	–.061
	(12.49)	(6.41)		
	θ=–1, ρ=.5, LLF=–6295.54			
Constant	.290	.172		
	(3.48)	(2.10)		
HS Graduate	–.225	.284	–.034	.121
	(3.11)	(4.20)		
GED	–.130	–.065	–.040	.034
	(.92)	(.51)		
AFQT Score	–1.004	–.210	–.282	.312
	(11.82)	(2.28)		
SQT Score	.096	.195	.043	–.003
	(4.52)	(9.43)		
SQT Level	.605	.922	.240	–.066
	(10.50)	(9.57)		
	θ=1, ρ=–.5, LLF=–6294.89			
Constant	.168	1.045		
	(2.09)	(12.88)		
HS Graduate	–.180	.422	–.033	.121
	(2.59)	(6.34)		
GED	–.122	.025	–.038	.033
	(.91)	(.19)		
AFQT Score	–.972	.473	–.289	.318
	(11.91)	(5.17)		
SQT Score	.113	.122	.044	–.004
	(5.66)	(5.96)		
SQT Level	.641	.453	.238	–.068
	(11.16)	(4.67)		

Appendix Table A-5
Reenlistment Model for Mechanical Maintenance

Explanatory Variable	Coefficients in Equation for R	Coefficients in Equation for Q	Derivative of Probability of Reenl	Derivative of Probability of NSep
	θ=1, ρ=.5, LLF=–4831.84			
Constant	–.240 (3.18)	1.420 (15.80)		
HS Graduate	.063 (1.02)	.504 (7.06)	.024	.072
GED	.205 (1.72)	.140 (.97)	.076	–.045
AFQT Score	–.586 (5.88)	.401 (3.08)	–.216	.278
SQT Score	.122 (5.81)	.126 (5.17)	.045	–.019
SQT Level	.643 (7.85)	.371 (2.66)	.239	–.154
	θ=–1, ρ=.5, LLF=–4831.05			
Constant	.140 (1.69)	.041 (.49)		
HS Graduate	–.097 (1.42)	.411 (6.20)	.015	.083
GED	.149 (1.14)	.220 (1.68)	.067	–.031
AFQT Score	–.724 (6.78)	.018 (.15)	–.211	.275
SQT Score	.092 (4.06)	.160 (6.96)	.044	–.016
SQT Level	.585 (6.83)	.648 (5.52)	.241	–.147
	θ=1, ρ=–.5, LLF=–4830.82			
Constant	.013 (.16)	.996 (12.15)		
HS Graduate	–.046 (.69)	.461 (7.05)	.016	.081
GED	.168 (1.31)	.094 (.72)	.069	–.033
AFQT Score	–.690 (6.64)	.548 (4.60)	–.216	.276
SQT Score	.107 (4.89)	.084 (3.75)	.046	–.018
SQT Level	.623 (7.17)	.179 (1.51)	.243	–.149

Appendix Table A-6
Reenlistment Model for Administration

Explanatory Variable	Coefficients in Equation for R	Coefficients in Equation for Q	Derivative of Probability of Reenl	Derivative of Probability of NSep
	θ=1, ρ=.5, LLF=–1895.35			
Constant	.748	1.296		
	(5.26)	(6.72)		
HS Graduate	–.295	.579	–.088	.169
	(2.30)	(3.41)		
GED	–.217	.275	–.069	.100
	(.88)	(.79)		
AFQT Score	–1.303	.586	–.448	.436
	(9.29)	(2.88)		
SQT Score	.178	.086	.066	–.033
	(5.75)	(2.12)		
SQT Level	.711	.643	.274	–.086
	(6.42)	(2.72)		
	θ=–1, ρ=.5, LLF=–1894.96			
Constant	1.239	.559		
	(7.96)	(3.39)		
HS Graduate	–.521	.211	–.049	.159
	(3.69)	(1.45)		
GED	–.353	.026	–.060	.101
	(1.32)	(.09)		
AFQT Score	–1.514	–.247	–.337	.411
	(10.18)	(1.36)		
SQT Score	.163	.159	.067	–.037
	(4.88)	(4.39)		
SQT Level	.618	.907	.322	–.121
	(5.43)	(4.66)		
	θ=1, ρ=–.5, LLF=–1895.31			
Constant	1.130	.677		
	(6.93)	(4.13)		
HS Graduate	–.481	.579	–.031	.155
	(3.23)	(4.03)		
GED	–.336	.275	–.048	.097
	(1.24)	(.92)		
AFQT Score	–1.479	.877	–.278	.401
	(9.98)	(4.85)		
SQT Score	.173	.035	.060	–.036
	(5.23)	(.96)		
SQT Level	.653	.476	.295	–.105
	(5.68)	(2.43)		

Comment

Sherwin Rosen

This paper promises to be a valuable addition to the literature on military manpower. The approach is interesting because it starts to model the joint decisions on both sides of the contract. Retention is a "marriage problem" where both parties must agree to continue the relationship. A person may desire to reenlist but the Army may deny the opportunity to continue service. Similarly, the Army may want to retain a person who prefers to leave. Two other situations exhaust the possibilities: unanimous agreement that the person either stay or leave.

The general problem is not at all unique to the military. It occurs in all employment relationships and has been extensively studied from the point of view of efficient turnover. That theory is an application of the economic principle that resources should flow to their highest valued uses. If this idea is followed rigorously, it suggests no real behavioral difference between "quits and layoffs," that is, between the two disagreement examples above. Consider the case where the employee wants to quit but the employer wants continuation of the contract. Ignore nonpecuniary factors for simplicity. Whether the worker should stay or leave depends only on whether current productivity on this job is greater than elsewhere. It is independent of current wages ("initial conditions"). If productivity is largest on the current job, then the employer can raise the wage high enough to make it worthwhile for the worker to stay. If productivity is larger on the other job, the means cannot be found to retain the worker on this one. The outcome is efficient in either case. Exactly the same reasoning applies when at the current wage, the firm wants to fire a worker who does not want to quit. In all cases the wage must change to resolve any disagreements and make the final decision agreeable to all concerned. Quit or layoff labels are arbitrary because they merely depend on the initial wage which is irrelevant for the actual turnover decision.

The larger problem of retention of military personnel is caused by an irrational pay schedule: it contains too few distinc-

tions among people and occupations for wages to properly perform their allocative function in the military. A sociological, egalitarian approach to military pay appropriate, if at all, to conscription still dominates military and Congressional thinking about compensation. Efficient turnover requires pay categories to be tailored to individual circumstances. Transactions cost and possible opportunism from people trying to "work" a complicated schedule to their own advantage reduce the optimal number of pay categories. Nonetheless, it is obvious that the current pay table makes not nearly enough distinctions between military occupations within ranks. Proof that this is so lies in the differential turnover observed among military jobs. Now, turnover rates across jobs need not be equal in an ideal system, but no one believes the current situation is desirable. Indeed, the military recognizes the problem by allowing selective reenlistment bonuses to discriminate among jobs. Why not educate Congress about the virtues of outright wage payments? The Army could design a relatively simple mechanism that would solve the problem once and for all: make wages in an MOS rise more than average when turnover is excessive and rise less than average when turnover is too small. This elegant method requires only internal administrative data to be made operational.

Making the appropriate qualifications for tastes, Brown suggests that the limited number of wage categories in the current system promotes excessive turnover among higher quality personnel. The point is a good one, but needs qualification for different jobs. If the pay in a grade is about right for the average job, some jobs for that grade will be overpaid on average and some will be underpaid on average. Turnover rates will differ across job categories. In the overpaid jobs it can happen that too many overqualified people are retained. In fact, overqualifications may substitute for wage competition when prices are not allowed to vary enough.

Another factor is important. Indivisibilities cause most organizations to use a slot system of allocating workers to jobs. The point is reinforced by the absence of price incentives on the demand side in determining the number of slots in military job categories. Then the Army's decision to retain or at least maintain eligibility for reenlistment in job categories can be

affected by the number of people employed in the category. Sensitivity of reenlistment bonuses to reported shortfalls or surpluses suggests the importance of examining this matter more closely. It might be investigated by incorporating job specific shortages or surpluses in the Q-selection function. They might also belong in the R-function. For example, surpluses of personnel in a job category may reduce promotion prospects in that category and discourage personnel from continuing. This is not so much criticism of Brown's basic approach, as a suggestion for a more elaborate specification for it. Perhaps these considerations can account for some of the differences he found among the three job categories and also for some of the changes in estimates over time within these categories.

My next point is more conceptual. In marriage problems the decision rules of both parties are almost surely interrelated in ways that are not really modeled here. Harvard gets few applicants from people whose IQs are in the range of 85–95, because they know they will not be admitted. When I asked my wife to marry me, I was pretty sure that she would say yes. Knowing the selection rule of the other party and knowing also whether one is eligible or not affects one's own selection rule.

Brown is aware of the point and attempts to deal with it in discussing who is actually marked eligible or ineligible and in the parameterization involving θ. But he does not really confront the issue directly. Admittedly, it is not clear how the Army determines its decision rules (though surplus or shortfall numbers must have some role in it, as above). However, it is the dominant player in this particular game. For that reason I would be inclined to pursue a Stackelberg leader kind of model in which the Army's decision rule is chosen as a reaction to the recruits' rules. Whatever that analysis might be, it would lead to some cross-equation restrictions in decision rules: the A and B vectors would not be independent of each other. As Brown emphasizes as well, strategic considerations lead to certain ambiguities in who actually gets an ineligible marker written in the record. The theory of efficient turnover suggests additional problems with those labels, which play a crucial role in identifying the A and B parameters in this paper. Yet only some 10 percent of the sample gets an ineligible marker. Since

almost all decisions are in agreement on both sides, there is not enough data to be very confident about how the effects get parceled out between the Q and R functions. The θ parameterization doesn't help much either; it makes little difference to the estimates. Ignoring strategic interactions, more information would come from a specification in which the Q and R functions had at least a few arguments that were in one function but not in the other. The opportunity wage belongs in R, but perhaps not in Q. The surplus or shortfall manpower situation belongs in Q, but perhaps not in R. In the strategic model, double exclusion restrictions would be more problematic.

For my final point I wish to raise a question. What determines the value of personnel quality in Army retention goals? Brown's estimates do suggest that high-quality people tend to leave earlier, but is this so bad? Why did these able people enter the military in the first place? Their AFQT scores and high school diplomas were known before they entered (this preselection does not enter Brown's statistical model, but I am skeptical that explicit treatment would affect the estimates very much). Surely we do not want to think of all first-term recruits as career personnel. Many intend to stay only for a limited period of time. For them the military is a part of the complicated transition process from school to civilian work. From the Army's point of view there is an optimum age distribution of personnel. For a very important part of Army operations the desired mean age is quite young and a fairly high turnover rate is optimal. Is it socially desirable for the most able recruits to remain in the military for several terms as opposed to pursuing other, nonmilitary careers? Can training and other commitments substitute for this kind of ability among those who remain? And what is it that the youth who join expect to get out of their term in the military? For many of them a relatively short term of Army service is part of the educational process during a critical time of life. The value of the permanent or temporary nature of the assignment might well vary with a recruit's life circumstances. These matters must be given more thought in determining the socially optimal selection rules and compensation policy for personnel retention in the Army.

6

First-Term Attrition and Reenlistment in the U.S. Army

John T. Warner
Gary Solon

I. Introduction

In the past decade much research has focused on the economics of the military labor market. Interest in this market derives from the military's role as the largest single employer in the U.S. economy, the large share of the military wage bill in the federal budget, and the national interest in maintaining high-quality military forces. Research has focused on three areas: initial enlistment supply, attrition during the initial enlistment, and reenlistment behavior at the first-term decision point and beyond.[1]

This paper presents an analysis of new data on first-term attrition and the first reenlistment decision. Our analysis uses a large data base on men who enlisted in Army Military Occupation Specialties (MOS) in Career Management Field (CMF) 11 (Infantry) between fiscal years 1974 and 1983. MOS 11 is the Army's most important occupation specialty, and studying cohorts that entered it during the 1974–83 period is especially fruitful because this period contains wide variations in possible determinants of attrition and reenlistment, including relative military pay, educational benefits, civilian labor market conditions, and the educational characteristics and racial composition of entering cohorts.

Our analysis devotes special attention to the issue of dynamic selection effects. Recent studies of successive reenlistment decisions, such as Gotz and McCall (1986) and Black, Hogan, and Sylwester (1987), have recognized that proper estimation of a model for reenlistment at one decision point must account for the impact of previous reenlistment outcomes on the distribution of unobservable characteristics in the population that reaches the present decision point. It is less commonly recognized that the same issue applies to the connections between first-term attrition and previous enlistment decisions and between reenlistment and previous attrition and enlistment outcomes.[2] Our models for attrition and reenlistment include variables likely to influence the distribution of unobserved characteristics in the initial enlistee population, and we estimate a joint model of attrition and reenlistment that explicitly incorporates the role of unobserved characteristics that may be correlated across the two processes.

Our analyses produce a wealth of results on determinants of first-term attrition and reenlistment. Some of the strongest patterns are that high school graduates are much more likely to survive the first term but less likely to reenlist, minorities are more likely to survive and to reenlist, and reenlistment decisions are responsive to the pecuniary attractiveness of Army versus civilian employment. We estimate that, other things being equal, the survival probability for high school graduates exceeds that for nongraduates by more than .15. When their lower reenlistment probability also is taken into account, however, high school graduates' probability of continuing to a second term is barely higher than that of nongraduates. Blacks' and Hispanics' probability of continuing to a second term is estimated to exceed that of non-Hispanic whites by more than .05, with the effect appearing mainly at the survival stage for blacks and mainly at the reenlistment stage for Hispanics. We find that the elasticity of reenlistment probability with respect to military pay is about unity.

Our exploration of dynamic selection effects yields mixed results. On one hand, we find that, once conditions at the time of reenlistment are controlled for, conditions at the time of initial enlistment that increase the supply of enlistees have a *perverse* effect on subsequent reenlistment decisions. For

example, enlistees drawn into the Army by depressed civilian labor market conditions are less likely to reenlist once the civilian market returns to normal. On the other hand, our parameter estimates for the reenlistment model are hardly affected by allowance for correlation of unobservables between the attrition and reenlistment models. This suggests that when the regressor set is relatively rich, the usual practice of ignoring the attrition process when estimating reenlistment models may not produce serious biases.

Section II of the paper explains our econometric models. while Section III describes the data base. Section IV provides a detailed presentation of our empirical results. Section V summarizes and discusses our findings.

II. Econometric Models

We assume that the ith enlistee in the cohort that entered the Army in year t remains in the Army through the end of his first term if his net utility from doing so is positive. Otherwise, he becomes an attrition case. We write his net utility as

$$U_{it} = V_{it} + G_{it} \tag{1}$$

where V_{it} is his net pecuniary gain from staying in the Army and G_{it} is his net nonpecuniary gain. The nonpecuniary gain encompasses the enlistee's taste for military versus civilian life and may include disutility from the effort required to meet minimum standards for retention in the Army. For example, a very low-ability enlistee might have a particularly negative value of G_{it} if meeting Army standards would be especially onerous for him. By defining G_{it} as the enlistee's net nonpecuniary gain *conditional on the effort necessary to meet minimum Army standards,* we "internalize" the Army's role in the attrition process into the enlistee's decision process.[3]

Suppose that V_{it} and G_{it} both can be expressed as regression functions of observable and unobservable characteristics of the enlistee and his cohort. In particular, let

$$V_{it} = \gamma' Z_{it} + u_{it} \tag{2}$$

and

$$G_{it} = \delta' W_{it} + v_{it} \tag{3}$$

where Z_{it} and W_{it} are vectors of observable regressors, γ and δ are the associated vectors of coefficients, and u_{it} and v_{it} are error terms reflecting effects of unobservable variables.

The separation of equations (2) and (3) emphasizes that any particular regressor may influence attrition via its relationship to either pecuniary or nonpecuniary gains. For example, previous research on attrition has found that enlistees who graduated from high school or who achieved relatively high scores on the Armed Forces Qualifications Test (AFQT) are more likely to complete their first term. Our model enables interpretation of this finding as the net effect of several underlying effects that may operate in different directions. On the one hand, those with high school diplomas or high AFQT scores typically would have better civilian employment opportunities. Accordingly, dummy variables for high school graduation and high AFQT scores would be associated with smaller pecuniary gains from remaining in the Army and therefore would enter Z_{it} in equation (2) with negative coefficients. On the other hand, those with high school diplomas or high AFQT scores typically are abler and would find it easier to meet Army standards. In addition, high school graduates, having demonstrated that they have the motivation and perseverence necessary to complete high school, might be expected to derive greater utility from fulfilling their commitment to complete their first term. Further, even within the same occupational category the Army may not randomly assign individuals to different jobs or locations. Rather, smarter, better educated enlistees may be assigned to more appealing jobs or locations. These considerations imply that dummy variables for high school graduation and high AFQT scores would enter W_{it} in equation (3) with positive coefficients. A finding, therefore, that such variables are positively associated with first-term survival can be interpreted as empirical evidence that the latter effects dominate the pecuniary effects.

As another example, consider the effects of educational benefits contingent upon completing the first term. Of course, more generous benefits provide a direct pecuniary incentive to complete the first term and therefore would enter equation (2) with a positive coefficient. A subtler effect is that higher benefits, by increasing the supply of potential enlistees, might

enable Army recruiters to screen applicants more selectively. If this greater selectivity involves merely recruiting higher proportions of high school graduates and high-AFQT scorers, then the resulting impact on survival will be mediated solely by those variables. But, if recruiters also screen applicants on ability or personality attributes that are positively related to G_{it} but are not observable to us as researchers, educational benefits will enter with a positive coefficient in equation (3) as well as equation (2).

The variables in Z_{it} and W_{it} might include characteristics of the enlistee's cohort as well as of the enlistee himself. Previous research on enlistment, such as Brown (1985), indicates that the supply of enlistees is greater when military pay is high relative to civilian pay and when the unemployment rate is high. Not only do these circumstances increase the pecuniary incentive to enlist but, if they persist through the enlistee's first term, they increase the incentive to remain in the Army. In that case, these variables would enter equation (2) with positive coefficients. Also, like high educational benefits, they might enable Army recruiters to select enlistees with unmeasured ability or taste characteristics positively associated with G_{it} in equation (3).

On the other hand, in an instance in which high relative military pay or high unemployment at enlistment does not persist during the cohort's first term, a perverse negative effect on survival might ensue. For example, individuals with little taste for the military who were induced to enlist by high pay might be especially prone to attrition if they are subsequently disappointed by deterioration in relative pay. A similar point applies to those induced to enlist by depressed conditions in the civilian labor market.

These examples merely illustrate the variety of avenues through which explanatory variables in Z_{it} and W_{it} might influence the probability of first-term survival. A more complete discussion of explanatory variables is given in Sections III and IV. Whatever variables are contained in Z_{it} and W_{it}, the ith enlistee in cohort t survives his first term if and only if

(4) $$U_{it} = \gamma' Z_{it} + \delta' W_{it} + u_{it} + v_{it} > 0.$$

Let $\varepsilon_{it} = u_{it} + v_{it}$ and $\beta' X_{it} = \gamma' Z_{it} + \delta' W_{it}$ where X_{it} contains all elements in either Z_{it} or W_{it} or both. Then we can write the probability of survival as

$$(5) \qquad \begin{aligned} P_{it} &= \Pr(\beta' X_{it} + \varepsilon_{it} > 0) \\ &= \mathrm{Prob}(\varepsilon_{it} > -\beta' X_{it}) \\ &= 1 - F(-\beta' X_{it}) \end{aligned}$$

where F( ) is the cumulative distribution function for the distribution of ε_{it} in the enlistee population. It should be clear that, when an explanatory variable belongs in both Z_{it} and W_{it}, estimation of equation (5) cannot separately identify the variable's γ and δ coefficients. For instance, it is not possible to disentangle the (possibly opposing) effects of high school graduation on pecuniary versus nonpecuniary gains from remaining in the Army. All that can be estimated is the combined *net* effect β.

To complete the model, one must specify a particular functional form for F( ). If, conditional on X_{it}, ε_{it} follows a standard normal distribution, then

$$(6) \qquad \begin{aligned} P_{it} &= 1 - \Phi(-\beta' X_{it}) \\ &= \Phi(\beta' X_{it}) \end{aligned}$$

where $\Phi(\,)$ denotes the standard normal cumulative distribution function. This gives a probit function for the probability of survival. The corresponding derivative of the survival probability with respect to the hth regressor X_{hit} is

$$(7) \qquad \begin{aligned} dP_{it} / dX_{hit} &= \beta_h \phi(\beta' X_{it}) \\ &= \beta_h \phi\left(\Phi^{-1}(P_{it})\right) \end{aligned}$$

where β_h is the coefficient of X_{hit} and $\phi(\,)$ is the standard normal density function. If instead ε_{it} follows a logistic distribution,

$$(8) \qquad \begin{aligned} P_{it} &= 1 - \exp(-\beta' X_{it}) / [\,1 + \exp(-\beta' X_{it})\,] \\ &= 1/[\,1 + \exp(-\beta' X_{it})\,] \\ &= \exp(\beta' X_{it})/[\,1 + \exp(\beta' X_{it})\,] \end{aligned}$$

In this logit model for the probability of survival,

$$(9) \qquad dP_{it} / dX_{hit} = \beta_h P_{it}(1 - P_{it}).$$

In Section IV, we use maximum likelihood methods to estimate both probit and logit models of first-term survival.

An alternative approach is to model a continuous-time hazard rate for attrition from the Army. The hazard rate at length of service y is defined as

$$h(y) = g(y) / [1 - G(y)], \tag{10}$$

where g( ) and G( ) are respectively the density and cumulative distribution functions for completed length of service. The hazard rate h(y) is thus the rate of exit from the Army at instant y conditional on having survived to that point.

A convenient specification that allows h(y) to vary with observable and unobservable characteristics of the enlistee is the "proportional hazard" model[4]

$$h_{it}(y) = \lambda(y) \exp(-\beta' X_{it})\, \varepsilon_{it}. \tag{11}$$

In this formulation, ε_{it} reflects unobservable characteristics of the enlistee that do not change over the course of his first term, and the "duration dependence" term $\lambda(y)$ represents effects of length of service thus far. Note that, if a particular explanatory variable has a positive β coefficient, an increase in that variable reduces the attrition hazard and therefore increases the probability of survival. The interpretation of the sign of the coefficient is thus the same as in the probit and logit models for first-term survival.

As shown in Lancaster (1979), if the distribution of ε_{it} in the enlistee population is a gamma distribution with mean zero and variance $1/\Theta$, the probability of surviving to instant y, conditional only on the observables X_{it}, is

$$1 - G_{it}(y) = [1 + I(y) \exp(-\beta' X_{it}) / \Theta\,]^{-\Theta} \tag{12}$$

where

$$I(y) = \int_0^y \lambda(u) du. \tag{13}$$

If y is measured in years, $\alpha_1 = \log I(1)$, and $\alpha_y = \log [I(y) - I(y-1)]$ for y = 2, 3, or 4, then the probability of surviving the first y years can be written as

$$(14) \qquad 1 - G_{it}(y) = \{1 + [\exp(\alpha_1) + \ldots + \exp(\alpha_y)] \exp(-\beta' X_{it}) / \Theta\}^{-\Theta}.$$

With y equated to the full length of the first term, equation (14) provides an alternative functional form, instead of the probit or logit, for the probability of surviving the first term. Indeed, this form nests the logit model as a special case; if $\Theta=1$, equation (14) simplifies to equation (8) with the α terms subsumed in the constant term. If equation (14) is used as the model for the survival probability P_{it}, the corresponding derivative of P_{it} with respect to the hth regressor X_{hit} is

$$(15) \qquad dP_{it} / dX_{hit} = \beta_h \Theta P_{it}(1 - P_{it})^{1/\Theta}.$$

The main advantage of this proportional hazard model, relative to the probit and logit models described above, is that it is easily adapted to exploit information on *when* attrition occurs, not just on *whether* it occurs. For example, in a sample of enlistees for three-year terms, one can characterize four possible outcomes: attrition in the first year, attrition in the second year, attrition in the third, and survival of the term. The corresponding contributions to the likelihood function—$G_{it}(1)$, $G_{it}(2) - G_{it}(1)$, $G_{it}(3) - G_{it}(2)$, and $1 - G_{it}(3)$—are easily derived from equation (14). In Section IV, by maximizing the resulting likelihood function, we obtain estimates of β, Θ, and the α parameters. This estimated model traces out the temporal pattern of attrition as well as whether or not attrition occurs.

Of course, the net utility framework used to generate models for the probability of first-term survival can be used also to generate models for the probability of reenlistment at the end of the first term. Just as we wrote the probability of first-term survival as equation (5)

$$P_{it} = \Pr(\beta' X_{it} + \varepsilon_{it} > 0),$$

we can write the probability of reenlistment for a second term as

$$(16) \qquad Q_{it} = \text{Prob}(\alpha' R_{it} + \eta_{it} > 0).$$

Like X_{it}, R_{it} includes variables associated with the net pecuniary gain from staying in the Army, the net nonpecuniary gain, or

both. A key measure of the pecuniary gain is the ACOL variable discussed in Section IV. Again, high school graduation and high AFQT scores should be negatively associated with the net pecuniary gain from staying in the Army (though ideally this effect should be captured by the ACOL variable), but positively associated with ease of meeting the Army's standards for retention (in this case, eligibility to reenlist). A difference from the survival context is that, once the first-term commitment has been fulfilled, high school graduation as a signal of a propensity to complete commitments may no longer be a positive predictor of staying in the Army. Another difference is that educational benefits, which provide an incentive to complete the first term, also provide an incentive to leave at the end of the initial enlistment to use the benefits. Also, a high unemployment rate at the *end* of the first term should increase the pecuniary incentive to reenlist. But, controlling for unemployment at the *end* of the term, the effect of high unemployment at the *beginning* of the term might be dominated by a perverse effect. In particular, high unemployment at accession might be expected to have induced initial enlistment by individuals with relatively little predilection for the Army, who then are less likely to reenlist once civilian labor market conditions have improved. Higher relative pay at accession may have similar perverse effects on reenlistment. Again, these examples only illustrate the complex variety of possible influences on reenlistment. A more complete discussion of explanatory variables is provided in Sections III and IV.

If the reenlistment error term η_{it} in equation (16) could be assumed independent of the survival error term ε_{it} in equation (5), the reenlistment model would be completed by a distributional assumption for η_{it}. Assuming normality leads to a probit model for reenlistment, which we estimate in Section IV. But because the unobservable variables underlying ε_{it} and η_{it} are likely to overlap, it may be important to allow ε_{it} and η_{it} to be correlated. A convenient approach is to assume they follow a bivariate standard normal distribution with correlation parameter ρ. This leads to a bivariate probit model for first-term survival and reenlistment.

Given the sequential nature of the process, three possible outcomes can be observed: attrition, survival and reenlistment, and survival without reenlistment. The probability of attrition is simply

$$1 - P_{it} = 1 - \Phi(\beta' X_{it}). \tag{17}$$

The probability of survival and reenlistment is

$$\int_{-\infty}^{\alpha' R_{it}} \int_{-\infty}^{\beta' X_{it}} m(\varepsilon, \eta \mid \rho)\, d\varepsilon\, d\eta \tag{18}$$

where m( ) is the bivariate standard normal density function. The probability of survival without reenlistment is

$$\int_{\alpha' R_{it}}^{\infty} \int_{-\infty}^{\beta' X_{it}} m(\varepsilon, \eta \mid \rho)\, d\varepsilon\, d\eta \tag{19}$$

In Section IV, we use maximum likelihood methods to estimate this joint model of survival and reenlistment.

III. The Data

The data for our analysis are drawn from a file on 30,355 men who enlisted for three- or four-year terms in the Career Management Field (CMF) 11 between fiscal years 1974 and 1983. The 30,355 men include 17,934 3-year obligors (3YOs) and 12,421 4-year obligors (4YOs).[5] Table 6.1 shows, for each fiscal entry year, several other sample characteristics: the percentages black and Hispanic, the percentage that graduated high school, the percentage in mental groups I–IIIA (AFQT score at least 50), the percentage over age 19, the percentage that entered under waiver from ordinary enlistment standards, the percentage married at accession, and the average months of waiting in the Delayed Entry Pool (DEP). At the beginning of the sample period most enlistments were direct accessions, but in more recent years the Army has smoothed accession flows by queueing applicants in the DEP.

The figures in Table 6.1 reveal remarkable variations over time in the characteristics of incoming cohorts. The minorities percentage grew considerably in the late 1970s before declining in the 1980s. The percentage that graduated from high school rose until 1978, dropped dramatically in 1979 and 1980 and

Table 6.1
Sample Characteristics by Entry Year

Year	% BL	% HISP	% HSG	%MG I–IIIA	% > 19	% WAIV	% MARR	DEP MO
1974	20.5	5.7	45.1	55.9	24.9	4.2	13.3	.1
1975	17.0	7.5	47.8	53.9	22.4	2.2	12.2	.4
1976	21.8	2.4	52.9	45.8	23.8	5.8	11.4	.8
1977	32.4	7.1	57.0	24.8	22.7	7.4	7.4	1.8
1978	32.1	8.8	69.1	27.0	25.5	7.1	6.1	2.6
1979	33.3	7.0	51.6	20.4	26.4	10.4	7.6	1.5
1980	23.3	4.6	38.4	19.3	27.7	12.6	8.5	1.1
1981	17.6	4.8	71.7	35.0	30.2	9.9	8.8	2.3
1982	19.3	4.7	83.7	39.8	34.0	10.4	9.6	2.0

then rose again dramatically in the 1981–83 period. The percentage in mental groups I–IIIA dropped to a low level in the 1977–80 period and then rebounded afterward. From the 1970s to the 1980s the percentages over age 19 and the percentages entering under waivers have increased while the percentage married has decreased. Average waiting time in the DEP generally increased over the period.

These changes in enlistee characteristics have been accompanied by, and presumably are related to, changes in the economic environment. Table 6.2 tracks the changes over time in relative military pay, the civilian unemployment rate, average educational benefits, and average enlistment bonus. The relative pay variable, constructed by Goldberg and Greenston (1986), is the present value of Army pay over a four-year period divided by the corresponding value of civilian earnings. The unemployment rate is the sample average of the annual (calendar year) unemployment rate in the enlistee's state of origin. Educational benefits (based on a present value calculation described elsewhere in this volume) and enlistment bonus are in 1980 dollars.

The table shows that relative military pay in 1979–80 was ten percent below its level in 1974–75 and educational benefits

Table 6.2
Mean Values of Economic Variables at Enlistment

Entry Year	Relative Military Pay	Civilian Unemploy-ment	Educational Benefits	Enlistment Bonus
1974	1.09	5.20	8,863	0
1975	1.09	5.86	8,693	0
1976	1.06	7.93	9,462	789
1977	1.04	7.18	5,355	1,053
1978	1.02	6.17	2,234	1,305
1979	.98	5.78	2,322	759
1980	.98	6.98	2,248	471
1981	1.05	7.60	2,679	264
1982	1.16	9.41	2,893	53
1983	1.21	9.74	3,304	319

were far lower as well.[6] This pattern dovetails with the relatively low 1979-80 percentages of high-quality recruits.[7] The dramatic rise in recruit quality after 1980 accompanied substantial increases in relative military pay and civilian unemployment and improvement in the educational benefits package.[8]

Table 6.3 shows, for each entry cohort, the rates of first-term survival and reenlistment for a second term.[9] These, too, show remarkable variation. The survival rate was unusually high in the 1977 and 1978 cohorts, declined in the 1979 and 1980 cohorts, and rose afterward. Reenlistment rates were unusually high in the 1978 and 1979 cohorts and returned to normal afterward. The econometric analyses in the next section are an effort to identify determinants of the variation in survival and reenlistment.

IV. Empirical Results

The first part of this section presents estimates of probit, logit, and proportional hazard models for the probability of

Table 6.3
Survival and Reenlistment Rates

Entry Year	Survival All	Survival 3-YO	Survival 4-YO	Reenlistment All	Reenlistment 3-YO	Reenlistment 4-YO
1974	58.8	57.3	61.0	27.1	19.9	38.3
1975	62.9	61.4	65.0	22.8	19.3	27.8
1976	58.0	53.5	63.8	25.9	21.2	30.8
1977	67.1	66.0	68.9	35.0	31.2	40.6
1978	72.0	69.5	74.4	43.2	39.4	46.6
1979	66.2	63.9	70.4	39.9	41.5	34.5
1980	62.3	61.0	65.6	25.2	22.6	32.0
1981	68.6	71.1	65.6	25.4	22.2	29.7
1982	70.0	71.6	68.3	25.2	21.5	29.1
1983	73.0	75.4	70.7	22.9	22.3	23.6

first-term survival. The second part presents results for the probability of reenlistment at the end of the first term. The third part presents estimates of a bivariate probit model for both survival and reenlistment.

First-Term Survival

This section begins with maximum likelihood estimates of probit equation (6) and logit equation (8) for the probability of completing the first term. Because estimating these nonlinear models for the full sample of 30,355 enlistees was computationally infeasible, we instead used randomly selected subsamples of 10,000 enlistees.

The regressor vector X_{it} contains a large set of explanatory variables. Among these are relative military pay at accession, the state unemployment rate at accession, educational benefits, enlistment bonus, and months in the DEP. Also included are dummy variables for high school graduation, mental groups I–IIIA, black, Hispanic, marital status at accession, entry under a waiver, enlistees over 19, and a three-year term.

The likely influences of some of these variables were discussed already in Section II. In addition, previous studies have found that survival rates are higher for blacks and Hispanics but lower for older enlistees and those already married at accession. The higher survival rates for blacks and Hispanics might reflect inferior civilian opportunities, which increase the net gain from Army service. Although married enlistees receive higher pay and more in-kind benefits, these pecuniary incentives to stay are apparently more than offset by nonpecuniary disadvantages or by higher civilian pay. Months in the DEP and entry under a waiver might both proxy for other unobservable determinants of survival. Enlistees who have waited in the DEP may be more likely to survive because they waited for relatively attractive Army jobs and because their willingness to wait signals a strong preference for military service. Those that enter under a waiver tend to be low-quality recruits who find it difficult to meet Army retention standards.

Additional explanatory variables are dummies for specific Infantry military occupational specialties in CMF 11 and for fiscal quarter of accession. The four specialties (MOS) in CMF 11 are the omitted category 11B (Infantryman), 11C (Indirect Fire Infantryman), 11H (Heavy Antiarmor Weapons Infantryman), and 11M (Fighting Vehicle Infantryman). The quarter dummies are included because Cymrot (1986) found evidence of higher attrition among third-quarter enlistees. Table 6.4 reports sample means for all the explanatory variables.

Estimates of probit and logit models of first-term survival are displayed in Tables 6.5 and 6.6, respectively. Each model is estimated for a random sample of 10,000 three-year obligors, a sample of 10,000 four-year obligors, and a pooled sample of 10,000. While the statistical significance of the estimated coefficients is indicated by the t-ratios in parentheses, interpreting the practical significance requires a little more work. As indicated in equation (7) in Section II, in the probit model the derivative of the survival probability with respect to the hth regressor is the regressor's coefficient times a standard normal density value. At a "typical" survival probability of about 2/3 (corresponding to the empirical survival rates in Table 6.3), the density value is about .36. Therefore, to convert the estimated probit coefficients into estimated derivatives, multiply them by

Table 6.4
Mean Values of Regressors

Variable	Pooled	3-YO	4-YO
%HSG	59.5	35.7	94.5
%MG I–IIIA	34.5	23.4	50.6
%Black	23.9	24.9	22.5
%Hispanic	5.9	6.9	4.8
%Married	9.0	7.7	11.1
%Waiver	8.5	8.4	8.3
%Age > 19	27.0	21.9	33.6
DEP Months	1.7	1.2	2.4
Educational Benefits	$4,645	$4,305	$5,086
Bonus Amount	$624	$103	$1,285
Unemployment at Accession	7.39	7.27	7.52
Relative Pay at Accession	1.057	1.050	1.067
FY Entry Qtr 1	20.7	22.0	18.6
FY Entry Qtr 2	22.9	25.2	19.7
FY Entry Qtr 3	23.0	22.8	23.3
MOS 11C	16.8	16.0	17.1
MOS 11H	6.9	6.0	8.0
MOS 11M	1.2	.9	1.5
%3-YO	60.9		
ACOL	$3,626	$3,380	$3,820
Unemployment at Reenlistment	7.49	7.63	7.34
Pay-grade Difference	.03	.05	.02

Table 6.5
Estimated Coefficients in Probit Models for First-Term Survival

Variable	Pooled	3-YO	4-YO
Intercept	–.006	.382	–.386
	(.03)	(1.69)	(1.55)
Black	.120	.067	.048
	(3.85)	(2.04)	(1.39)
Hispanic	.257	.199	.278
	(2.40)	(3.69)	(4.21)
Married at Accession	–.215	–.205	–.194
	(4.47)	(4.10)	(4.43)
High School Graduate	.479	.493	.500
	(12.92)	(15.38)	(12.29)
Mental Group I–IIIA	.059	–.002	.076
	(1.87)	(.07)	(2.54)
Waiver to Enlist	–.100	–.093	–.158
	(2.12)	(1.99)	(3.36)
Months in DEP	.026	.021	.032
	(4.84)	(3.33)	(6.65)
EducationalBenefits ($1,000)	–.009	–.011	–.004
	(1.62)	(2.68)	(.83)
Bonus Amount ($1,000)	–.002	–.047	.004
	(.13)	(1.38)	(.38)
Unemployment at Accession	–.011	–.003	–.021
	(1.63)	(.42)	(2.99)
Relative Military Pay at Accession	–.003	–.196	.411
	(.01)	(.83)	(1.64)
Age >19 at Accession	–.014	.060	–.066
	(.43)	(1.76)	(2.15)
FY Entry Qtr 1	.093	.117	.034
	(2.42)	(3.07)	(.88)
FY Entry Qtr 2	.001	0.019	.000
	(.05)	(.50)	(.00)
FY Entry Qtr 3	–.068	–.065	–.089
	(1.87)	(1.76)	(2.50)
3-Year Obligor	.248		
	(6.15)		
MOS 11C	.086	.172	.115
	(2.41)	(4.72)	(3.24)
MOS 11H	.361	.399	.289
	(6.48)	(6.66)	(5.62)
MOS 11M	.459	.515	.466
	(3.35)	(3.09)	(3.76)
Log-Likelihood	–6,210.5	–6,234.1	–6,142.6
Sample Size	10,000	10,000	10,000

Table 6.6
Estimated Coefficients in Logit Models for First-Term Survival

Variable	Pooled	3-YO	4-YO
Intercept	−.021	.612	−.644
	(.06)	(1.63)	(1.55)
Black	.195	.110	.082
	(3.78)	(2.03)	(1.43)
Hispanic	.433	.334	.464
	(2.40)	(3.67)	(4.12)
Married at Accession	−.350	−.330	−.314
	(4.49)	(4.04)	(4.42)
High School Graduate	.789	.812	.809
	(12.75)	(15.18)	(8.82)
Mental Group I–IIIA	.093	−.005	.127
	(1.81)	(.10)	(2.58)
Waiver to Enlist	−.160	−.149	−.257
	(2.10)	(1.95)	(3.33)
Months in DEP	.044	.036	.053
	(4.86)	(3.25)	(6.52)
Educational Benefits ($1,000)	−.014	−.019	−.006
	(2.05)	(2.72)	(.36)
Bonus Amount ($1,000)	.004	−.074	.007
	(.16)	(1.29)	(.87)
Unemployment at Accession	−.018	−.005	−.034
	(1.62)	(.42)	(2.99)
Relative Military Pay at Accession	−.001	−.317	.679
	(.03)	(.81)	(1.63)
Age >19 at Accession	−.020	.100	−.108
	(.38)	(1.78)	(2.14)
FY Entry Qtr 1	.158	.195	.058
	(2.49)	(2.89)	(.89)
FY Entry Qtr 2	.004	.030	.002
	(.07)	(.51)	(.03)
FY Entry Qtr 3	−.108	−.106	−.145
	(1.83)	(1.76)	(2.48)
3-Year Obligor	.413		
	(6.13)		
MOS 11C	.140	.283	.192
	(2.39)	(4.69)	(3.23)
MOS 11H	.600	.665	.486
	(6.33)	(6.54)	(5.55)
MOS 11M	.779	.921	.795
	(3.21)	(2.89)	(3.63)
Log-Likelihood	−6,210.5	−6,233.7	−6,142.0
Sample Size	10,000	10,000	10,000

.36. A similar analysis based on equation (9)'s expression for the derivative in a logit model indicates that estimated derivatives can be obtained by multiplying the estimated logit coefficients by .22. One would therefore expect the coefficient estimates from the logit model to be about .36/.22 = 1.6 times those from the probit model. A perusal of Tables 6.5 and 6.6 confirms that this is the case and also that the t-ratios for the two models are very similar.

Consistent with prior studies, the strongest result in the tables is that high school graduates are far more likely than nongraduates to survive the first term. The estimated coefficients imply that the difference in survival probability between graduates and nongraduates exceeds .15. This result corresponds to the patterns in Tables 6.1 and 6.3. The four entry cohorts with the smallest percentages of high school graduates —1974, 1975, 1979, and 1980—also had the lowest survival rates. The five with the highest high school graduate percentages—1977, 1978, 1981, 1982, and 1983—also had the highest survival rates. In Section II two reasons were advanced for a positive relationship between survival and high school graduation. One was that graduates are abler and find it easier to meet Army retention standards. Another was that graduates more typically possess the motivation and perseverence necessary for finishing whatever they begin. The second interpretation is supported by the much smaller estimated coefficients of the dummy variable for mental groups I–IIIA. Apparently, motivation, rather than ability, is the more crucial factor.

Our results, like those in previous studies, indicate that minorities are more likely to complete their enlistments. This finding is especially pronounced for Hispanics, whose survival probability is estimated to exceed that of non-Hispanic whites by about .1. Also in accordance with previous studies, we find that those married at accession have a lower survival probability. As conjectured, the survival probability is associated positively with months in the DEP and negatively with entry under a waiver. We also find that the survival probability is relatively high in the 11H and 11M specialties. Although we find some evidence of quarter effects similar to Cymrot's, they are small in magnitude. In our data age does not appear to have much influence on the survival probability.

At first glance, the economic variables—relative pay, unemployment at accession, educational benefits, and the bonus amount—appear to be more or less unrelated to the survival probability. Their coefficient estimates are often statistically insignificant and generally are small in magnitude. These estimates, however, are of *partial* effects once quality indicators like high school graduation, mental group, and months in the DEP have been controlled for. The absence of partial effects does not deny that the economic variables have important "reduced-form" effects. If, as enlistment studies indicate, more attractive military compensation and higher civilian unemployment increase the supply of high-quality enlistees, and if, as our results indicate, high-quality enlistees are more likely to survive, the economic variables do matter.[10] The absence of partial effects does refute one hypothesis put forth in Section II. We conjectured that economic conditions favorable to recruiting might enable recruiters to screen applicants more selectively, not only with respect to measurable characteristics like high school graduation but also unmeasurable ones that might also influence survival. We find little support for that conjecture.[11]

The probit and logit results in Tables 6.5 and 6.6 describe the effects of explanatory variables on the probability of attrition, but they do not use information on *when* attrition occurs. To incorporate such information, we have estimated the proportional hazard model described in Section II. The results are shown in Table 6.7.

The interpretation of coefficients of explanatory variables is facilitated by the derivative formula in equation (15) in Section II. Evaluating at a "typical" survival probability P_{it} = 2/3 and the .32 estimate of the heterogeneity parameter , the coefficient estimates for the three-year sample should be multiplied by .15 to convert them into estimated derivatives. For the four-year sample, in which Θ is estimated at .72, the coefficient estimates should be multiplied by .21. Once the coefficient estimates are rescaled in this way, the implied derivatives are generally quite similar to those implied by the probit and logit results. The logit model's implicit assumption that $\Theta = 1$, however, is rejected at any conventional significance level by a

Table 6.7
Estimated Parameters in Proportional Hazard Models for First-Term Survival

Variable	3-YO	4-YO
Black	.238	.084
	(3.31)	(1.44)
Hispanic	.407	.447
	(3.57)	(3.95)
Married at Accession	–.430	–.244
	(3.79)	(3.25)
High School Graduate	1.037	.846
	(14.95)	(8.76)
Mental Group I–IIIA	.049	.143
	(.69)	(2.83)
Waiver to Enlist	–.224	–.225
	(2.15)	(2.76)
Months in DEP	.046	.054
	(3.44)	(6.61)
Educational Benefits ($1,000)	–.057	–.019
	(6.04)	(.52)
Bonus Amount ($1,000)	–.136	–.010
	(1.77)	(.52)
Unemployment at Accession	–.005	–.032
	(.34)	(2.62)
Relative Military Pay at Accession	.131	.653
	(.26)	(1.51)
Age > 19 at Accession	.078	.169
	(1.05)	(3.26)
FY Entry Qtr 1	.496	.141
	(5.64)	(2.02)
FY Entry Qtr 2	.189	.057
	(2.38)	(.88)
FY Entry Qtr 3	–.131	.130
	(1.64)	(2.16)
MOS 11C	.530	.261
	(6.48)	(4.17)
MOS 11H	.940	.577
	(7.19)	(6.12)
MOS 11M	1.242	.961
	(3.20)	(3.22)
α_1	–1.616	–.970
	(3.32)	(2.24)
α_2	–.372	–.338
	(.76)	(.77)
α_3	–.918	–.432
	(1.87)	(.99)
α_4		–1.206
		(2.75)
θ	.32	.72
Log-Likelihood	–9,737.46	–10,305.52
Sample Size	10,000	10,000

likelihood ratio test with the three-year sample. The hypothesis $\Theta = 1$ is not rejected with the four-year sample.[12]

The main advantage of the proportional hazard results is that they trace out the temporal pattern of attrition. As an illustration, we have used the parameter estimates in Table 6.7 to calculate estimated yearly survival probabilities for each of the 17,934 three-year obligors and 12,421 four-year obligors in our complete sample. The sample means of these probabilities, which track the actual survival rates closely, are shown in Table 6.8. Among three-year obligors, the estimated proportion surviving the first year is .875, the estimated proportion surviving the second year is .697, and the estimated proportion completing the term is .644. The implied yearly attrition rates are .125 in the first year, $1 - .697/.875 = .203$ in the second year, and $1 - .644/.697 = .076$ in the last year. The nonmonotonic pattern in the yearly attrition rates reflects the nonmonotonic pattern in the estimated α's in Table 6.7. This nonmonotonicity in the estimated duration dependence parameters suggests that models that assume monotonicity, such as the Weibull model estimated in Baldwin and Daula (1985a), are ill-suited for analyzing attrition from the Army. The four-year sample's results in Tables 6.7 and 6.8 also display strong nonmonotonicity.

Of course, it is possible to use the estimates in Table 6.7 to explore the effects of changes in explanatory variables. For example, we have reestimated the three-year sample's survival rates with everyone's high school graduate dummy set to 1. This simulation, which estimates the *ceteris paribus* effects of shifting to an all-high-school graduate force, shifts the yearly

Table 6.8
Estimated Yearly Survival and Hazard Rates

	3-YO		4-YO	
Year	**Survival**	**Hazard**	**Survival**	**Hazard**
1	.875	.125	.910	.090
2	.697	.203	.787	.135
3	.644	.076	.707	.102
4			.676	.043

survival rates from .875, .697, and .644 to .931, .793, and .743. These results echo, now in a year-by-year form, our earlier finding that high school graduates have much higher survival rates.

Reenlistment

This subsection reports maximum likelihood estimates of the probit version of equation (10) for the probability of reenlisting at the end of the first term. For each of the three-year obligors, four-year obligors, and the pooled sample, this model is estimated for the sample members in the survival analysis that did survive their first term. Thus, the samples of size 10,000 for the survival analysis lead to samples of about 6,500 for the reenlistment analysis.

One issue that needs to be addressed here is the question of how to treat those who complete their enlistments but whom the Army declares ineligible to reenlist for failure to meet criteria for reenlistment. Over the data period approximately one quarter of those completing their enlistments were declared ineligible. Ineligibility may arise for a variety of reasons: failure to achieve the paygrade of E-4, drug abuse, shirking, etc. Ineligibility rates might also vary across entry cohorts as the Army changes eligibility standards in an effort to control reenlistment flows, though we are told that the Army did not change explicit eligibility standards over the data period.

Some reenlistment studies have restricted their analysis to those eligible to reenlist, but we do not do so. Our concern is that eligibility is not exogenous to the individual but rather depends partly on the individual's own behavior. As in the survival process, those individuals who do not wish to stay in the Army may not exert the effort required to meet eligibility standards. We therefore do not want to exclude ineligibles from our analysis because doing so would lead to a form of sample selection bias. For completeness, however, we have performed separate probit analyses of reenlistment eligibility, and reenlistment conditional on eligibility, the results of which are presented in Tables 6.9 and 6.10.

Table 6.9
Estimated Coefficients of Probit Models for Reenlistment Eligibility

Variable	Pooled	3-YO	4-YO
Intercept	.408	–.371	.459
	(31.95)	(28.85)	(35.25)
Black	–.141	–.107	–.085
	(2.80)	(2.28)	(3.22)
Hispanic	.054	–.044	–.009
	(.20)	(.62)	(1.05)
Dependents at Reenlistment	.064	.086	.012
	(3.05)	(3.94)	(1.57)
High School Graduate	.224	.234	.256
	(4.54)	(5.49)	(2.93)
Mental Group I–IIIA	–.022	.051	–.134
	(.49)	(1.12)	(2.83)
Waiver to Enlist	–.116	–.017	–.161
	(1.80)	(.28)	(2.33)
Months in DEP	.039	.043	.013
	(5.26)	(5.34)	(1.87)
Educational Benefits ($1,000)	–.002	–.008	.007
	(1.29)	(.95)	(.77)
Bonus Amount ($1,000)	.016	–.035	.008
	(.75)	(.79)	(.50)
Unemployment at Accession	–.028	–.031	–.002
	(2.98)	(3.26)	(.18)
Relative Military Pay at Accession	1.099	1.291	.695
	(2.89)	(3.18)	(1.78)
Age >19 at Accession	–.017	.028	–.009
	(.39)	(.64)	(.19)
FY Entry Qtr 1	–.015	–.120	–.011
	(.30)	(2.44)	(.22)
FY Entry Qtr 2	.122	.018	.024
	(2.44)	(.39)	(.45)
FY Entry Qtr 3	–.008	.139	–.016
	(.17)	(2.89)	(.31)
3-Year Obligor	–.177		
	(3.08)		
MOS 11C	–.045	–.021	–.098
	(.98)	(.48)	(2.00)
MOS 11H	.029	.138	–.054
	(.43)	(1.92)	(.89)
MOS 11M	–.003	.044	.065
	(.01)	(.25)	(.39)
ACOL ($1,000)	.082	.059	.124
	(3.13)	(2.41)	(3.96)
Unemployment Rate at Reenlistment	–.034	–.020	–.085
	(1.43)	(.85)	(3.22)
Pay-grade Difference	.730	.779	.805
	(17.09)	(18.01)	(18.49)
Log-Likelihood	–9,741.8	–10,114.6	–9,173.9
Sample Size	6,584	6,446	6,769

Table 6.10
Estimated Coefficients in Probit Models for First-Term Reenlistment (Conditional on Reenlistment Eligibility)

Variable	Pooled	3-YO	4-YO
Intercept	.408	5.117	–.628
	(31.58)	(8.76)	(1.29)
ACOL ($1,000)	.059	.052	.056
	(2.21)	(1.90)	(2.02)
Unemployment Rate at Reenlistment	–.068	–.198	.061
	(2.70)	(7.27)	(2.47)
Pay-grade Difference	.036	.046	.048
	(.78)	(.88)	(1.18)
Black	.509	.459	.564
	(9.69)	(8.48)	(10.64)
Hispanic	.086	.112	.098
	(1.10)	(1.47)	(1.02)
Dependents at Reenlistment	.172	.135	.188
	(8.15)	(5.59)	(10.24)
High School Graduate	–.272	–.284	–.695
	(4.93)	(3.98)	(7.36)
Mental Group I–IIIA	–.187	–.232	–.176
	(3.92)	(4.30)	(4.03)
Waiver to Enlist	–.047	–.008	.002
	(.66)	(.11)	(.04)
Months in DEP	.015	.018	.004
	(2.06)	(2.08)	(.61)
Educational Benefits ($1,000)	–.016	–.052	.011
	(1.77)	(5.59)	(1.23)
Bonus Amount ($1,000)	.020	.037	.009
	(.87)	(.63)	(.57)
Unemployment at Accession	–.033	–.026	–.017
	(3.20)	(2.30)	(1.77)
Relative Military Pay at Accession	–1.709	–3.581	–.314
	(4.41)	(8.55)	(.87)
Age >19 at Accession	.096	.088	.029
	(2.12)	(1.82)	(.70)
FY Entry Qtr 1	.062	.056	.034
	(1.16)	(.98)	(.67)
FY Entry Qtr 2	.121	.070	.000
	(2.28)	(1.29)	(.00)
FY Entry Qtr 3	.066	.000	.085
	(1.27)	(.00)	(1.79)
3-Year Obligor	–.207		
	(3.50)		
MOS 11C	–.046	.005	–.086
	(.93)	(.10)	(1.83)
MOS 11H	–.086	–.066	–.115
	(1.21)	(.86)	(1.78)
MOS 11M	.052	–.077	–.043
	(.35)	(.39)	(.32)
Log-Likelihood	–3,093.4	–2,776.5	–3,514.6
Sample Size	4,980	4,507	5,579

The regressor vector R_{it} in the reenlistment equation contains the same variables as in the survival model (except that number of dependents at reenlistment replaces marital status at accession) plus three new ones: the ACOL variable, the national annual (calendar year) unemployment rate at reenlistment, and a "pay-grade difference" variable that measures the enlistee's speed of promotion in his first term. The sample means of these variables for those who survive to reenlistment appear at the bottom of Table 6.4. The ACOL variable, described in Warner and Goldberg (1984) and refined in other papers in this volume, is an elaborate imputation of the net pecuniary present value of reenlisting. This variable, of course, is expected to be positively associated with the probability of reenlistment. Similarly, higher civilian unemployment might raise the net pecuniary value of remaining in the Army and therefore increase the probability of reenlistment. The pay-grade difference, also described in detail elsewhere in this volume, is simply the difference between the individual's pay grade at reenlistment and the average grade at that point for his cohort. Since the impact of pay-grade on the individual's potential military earnings is explicitly incorporated in the ACOL variable, the pay-grade difference variable by itself reflects the quality of the individual's match with the Army and is likely to be positively associated with probability of reenlistment.

Table 6.11 reports the estimated probit coefficients. At a "typical" reenlistment probability of about .3 (corresponding to the reenlistment rates in Table 6.3), the standard normal density value is about .35. Therefore, to convert the estimated probit coefficients into estimated derivatives, multiply them by .35.

As expected, the estimated coefficients of the ACOL variable are significantly positive in all three samples. The estimates are clustered around .07, which, evaluated at sample means, implies that the elasticity of the reenlistment probability with respect to ACOL is about .3. Given that the elasticity of ACOL with respect to military pay is about 4, this implies a pay elasticity of reenlistment of approximately 1.2.

Also as expected, pay-grade difference shows a significant and large positive association with reenlistment probability.

Table 6.11
Estimated Coefficients in Probit Model for First-Term Reenlistment

Variable	Pooled	3-YO	4-YO
Intercept	1.333	3.522	–.912
	(2.80)	(6.88)	(2.01)
ACOL ($1,000)	.065	.065	.076
	(2.71)	(2.68)	(2.94)
Unemployment Rate at Reenlistment	–.074	–.175	.022
	(3.33)	(7.42)	(.99)
Pay-grade Difference	.270	.355	.274
	(6.61)	(7.95)	(7.36)
Black	.372	.323	.420
	(7.97)	(6.88)	(8.68)
Hispanic	.090	.084	.082
	(1.28)	(1.25)	(1.12)
Dependents at Reenlistment	.159	.142	.162
	(8.44)	(6.70)	(9.97)
High School Graduate	–.148	–.152	.010
	(3.01)	(3.55)	(1.21)
Mental Group I–IIIA	–.173	–.176	–.193
	(4.03)	(3.70)	(4.79)
Waiver to Enlist	–.063	–.005	–.053
	(.99)	(.08)	(.84)
Months in DEP	.023	.028	.007
	(3.59)	(3.57)	(1.20)
Educational Benefits ($1,000)	–.017	–.046	.011
	(2.20)	(5.77)	(1.36)
Bonus Amount ($1,000)	.027	.007	.016
	(1.38)	(.16)	(1.09)
Unemployment at Accession	–.034	–.033	–.015
	(3.64)	(3.32)	(1.68)
Relative Military Pay at Accession	–1.180	–2.592	–.068
	(3.34)	(6.98)	(.20)
Age >19 at Accession	.080	.077	.020
	(1.96)	(1.81)	(.54)
FY Entry Qtr 1	.050	.002	.017
	(1.04)	(.06)	(.36)
FY Entry Qtr 2	.148	.073	.004
	(3.10)	(1.54)	(.08)
FY Entry Qtr 3	.046	–.053	.057
	(.98)	(1.08)	(1.32)
3-Year Obligor	–.236		
	(4.35)		
MOS 11C	–.045	.003	–.096
	(1.01)	(.08)	(2.22)
MOS 11H	–.041	–.004	–.100
	(.30)	(.06)	(1.83)
MOS 11M	.041	–.057	–.032
	(.29)	(.31)	(.26)
Log-Likelihood	–3,743.7	–3,525.8	–4,085.3
Sample Size	6,584	6,446	6,769

Contrary to expectation, the unemployment rate at reenlistment has a significantly *negative* coefficient estimate in two of the samples. A potential explanation is that, when unemployment is high and new recruits are readily available, the Army raises its eligibility standards for reenlistment. The probit results for reenlistment eligibility, however, do not indicate strong unemployment rate effects on reenlistment eligibility for the two samples that show strong negative effects of unemployment on reenlistment. The possibility remains, though, that when unemployment is high, the Army discourages reenlistment through means other than official reenlistment eligibility standards.

Minorities are more likely to reenlist, as well as to survive the first term. The association is especially large for blacks, whose estimated reenlistment probability exceeds that of whites by more than .1.[13] This corresponds to the fact, displayed in Tables 6.1 and 6.3, that the 1977–79 enlistee cohorts, which had by far the highest percentages of blacks, also had by far the highest reenlistment rates. The large estimated race effect on reenlistment probability suggests that the ACOL variable may not be fully capturing the inferior civilian opportunities of blacks. Another survival effect that persists into reenlistment is the positive effect of months in the DEP.

High school graduates, who have a much higher probability of surviving the first term, have a significantly lower probability of reenlisting, especially among three-year obligors. Enlistees in mental groups I to IIIA also are less likely to reenlist. Apparently, as discussed in Section II, once the first term is completed, the pecuniary effects of these variables come to dominate. This is somewhat surprising because, in principle, the ACOL variable should absorb the impact of the pecuniary incentives. An additional factor may be that high school graduates and high-AFQT scorers are especially likely to enlist (and survive) in order to qualify for eduational benefits and then to leave in order to use them. Indeed, high school graduation is positively related to eligibility to reenlist, but negatively related to choice to reenlist conditional on eligibility. As expected, the educational benefits variable has a significantly negative association with reenlistment probability, which, like the high school graduation effect, is concentrated

among three-year obligors. It stands to reason that those who enlist to qualify for and then use educational benefits would prefer the shorter term.

Finally, as conjectured in Section II, once conditions at the reenlistment point are controlled for, high relative military pay and unemployment at the time of *accession* have perverse effects on *reenlistment*. Holding constant the unemployment rate at reenlistment, higher unemployment at accession tends to draw in enlistees who do not reenlist when civilian labor market conditions return to normal.[14] Similarly, holding constant ACOL at reenlistment, higher pay at accession tends to draw in enlistees who do not reenlist when the pecuniary incentives to stay in the Army are no longer so strong. An important result, however, is that relative pay at accession is significantly and positively related to reenlistment eligibility.

Bivariate Models for Survival and Reenlistment

As discussed in Section II, a separate probit model for reenlistment is appropriate only if the reenlistment error term η_{it} is uncorrelated with the survival error term ε_{it}. An assumption of zero correlation is a strong restriction because ε_{it} and η_{it} reflect unobservable characteristics that influence pecuniary and nonpecuniary gains from staying in the Army at different stages, and these characteristics are likely to carry over from one stage to the next. If ε_{it} and η_{it} are correlated, ignoring that correlation in the estimation of the reenlistment model amounts to ignoring self-selection at the survival stage, which determines the pool of enlistees that reach the reenlistment decision point. Such disregard of sorting across the distribution of unobserved heterogeneity generally causes inconsistent parameter estimation, as has been amply discussed in the general literature on econometric duration models[15] and the specific literature on successive military reenlistment decisions.[16]

Therefore, in this subsection, we allow for correlation between ε_{it} and η_{it} by adopting the bivariate probit model discussed in Section II. We have estimated the model by maximum likelihood, using equations (17)–(19) in Section II as the contributions to the likelihood function. Computational

constraints have limited us to using a random subsample of 9,000 enlistees for the pooled analysis of three- and four-year obligors and random subsamples of 10,000 for the separate analyses. Also, we have reduced the size of the regressor vectors by dropping age and bonus amount from the survival model and dropping months in the DEP and the dummy variables for waiver, entry quarter, and MOS subgroup from the reenlistment model.

The first panels of Tables 6.12, 6.13, and 6.14 show estimates based on the restriction that the correlation ρ between ε_{it} and η_{it} equals zero. These, in effect, are estimates of separate probit models for survival and reenlistment based on the new samples and the smaller regressor vectors. Comparison of these estimates to those in Tables 6.5 and 6.9 reveals that the changes in samples and regressors generally have little effect on the results previously discussed.

The second panels report the results of analyses in which ρ is estimated jointly with the other parameters. In all three samples, the estimated ρ is insignificantly negative. The large standard error estimates underlying the small t-ratios indicate that we are unable to estimate ρ accurately. This weak identification of ρ is unsurprising given the absence of powerful exclusion restrictions. The difficulty of identifying ρ in a censored bivariate probit model has been noted previously by Danzon and Lillard (1982) and is a close cousin of the well-known difficulty of identifying sample selection effects in a linear regression model.[17] The most important result in the tables, however, is that allowance for nonzero ρ has almost no effect on most of the estimated coefficients. The only change large enough to be worth mentioning is that, in the pooled and three-year samples, the negative association between reenlistment and high school graduation becomes even larger. Otherwise, the robustness of the results suggests that the usual practice of ignoring selection at the survival stage in the estimation of reenlistment models does not necessarily produce serious biases.

This conclusion should be taken with two grains of salt. First, although allowing for correlation between unobservables has little effect on our results, we have an unusually

Table 6.12
Estimated Coefficients in Bivariate Probit Model for First-Term Survival and Reenlistment, Pooled Sample of Three- and Four-Year Obligors

Variable	Survive	Reenlist	Survive	Reenlist
ρ	0		−.227	
			(1.14)	
Intercept	.018	1.011	.026	1.203
	(.07)	(2.03)	(.11)	(2.32)
Black	.058	.378	.058	.366
	(1.69)	(7.87)	(1.69)	(7.36)
Hispanic	.277	.017	.277	−.016
	(3.62)	(.19)	(3.62)	(.16)
Married at Accession	−.176		−.138	
	(3.68)		(2.85)	
Dependents at Reenlistment		.162		.164
		(8.18)		(8.35)
High School Graduate	.444	−.133	.444	−.191
	(11.59)	(2.59)	(11.59)	(2.63)
Mental Group I–IIIA	.041	−.158	.041	−.161
	(1.25)	(3.53)	(1.26)	(3.64)
Waiver to Enlist	−.138		−.142	
	(2.84)		(2.93)	
Months in DEP	.029		.036	
	(5.27)		(5.56)	
Educational Benefits ($1,000)	−.010	−.011	−.010	−.009
	(2.15)	(1.31)	(2.13)	(1.08)
Unemployment at Accession	−.013	−.031	−.013	−.029
	(1.74)	(3.27)	(1.76)	(2.96)
Relative Military Pay at Accession	.053	−1.010	.041	−1.040
	(.22)	(2.81)	(.16)	(2.92)
Age >19 at Accession		.026		.032
		(.61)		(.76)
FY Entry Qtr 1	.109		.111	
	(2.70)		(2.75)	
FY Entry Qtr 2	−.030		−.019	
	(.79)		(.50)	
FY Entry Qtr 3	−.118		−.114	
	(3.15)		(3.05)	
3-Year Enlistee	.191	−.230	.192	−.236
	(5.10)	(4.11)	(5.10)	(4.00)
MOS 11C	.113		.108	
	(3.03)		(2.89)	
MOS 11H	.357		.345	
	(6.13)		(5.93)	
MOS 11M	.378		.381	
	(2.65)		(2.61)	
ACOL ($1,000)		.071		.068
		(2.81)		(2.73)
Unemployment Rate at Reenlistment		−.049		−.049
		(2.15)		(2.14)
Pay-grade Difference		.298		.292
		(6.94)		(6.74)
Log-Likelihood	−8,978.00		−8,977.50	
Sample Size	9,000		9,000	

Table 6.13
Estimated Coefficients in Bivariate Probit Model for First-Term Survival and Reenlistment, Sample of Three-Year Obligors

Variable	Survive	Reenlist	Survive	Reenlist
ρ	0		−.227 (1.13)	
Intercept	.363 (1.61)	5.086 (8.82)	.370 (1.56)	3.516 (7.02)
Black	.072 (2.23)	.323 (6.94)	.072 (2.19)	.309 (6.32)
Hispanic	.204 (3.79)	.086 (1.28)	.202 (3.76)	.059 (.83)
Married at Accession	−.182 (3.77)		−.179 (3.71)	
Dependents at Reenlistment		.140 (6.62)		.142 (6.81)
High School Graduate	.501 (15.84)	−.125 (3.02)	.499 (15.76)	−.188 (2.74)
Mental Group I–IIIA	−.000 (.02)	−.166 (3.50)	.002 (.08)	−.164 (3.49)
Waiver to Enlist	−.087 (1.86)		−.087 (1.89)	
Months in DEP	.020 (3.11)		.022 (3.51)	
Educational Benefits ($1,000)	−.013 (3.00)	−.048 (6.06)	−.013 (2.99)	−.046 (5.44)
Unemployment at Accession	−.003 (.41)	−.033 (3.34)	−.003 (.42)	−.031 (3.22)
Relative Military Pay at Accession	−.171 (.72)	−2.458 (6.78)	−.178 (.76)	−2.431 (6.70)
Age > 19 at Accession		.061 (1.45)		.063 (1.61)
FY Entry Qtr 1	.115 (3.05)		.114 (3.01)	
FY Entry Qtr 2	.016 (.43)		.022 (.60)	
FY Entry Qtr 3	−.066 (1.81)		−.070 (1.91)	
MOS 11C	.173 (4.75)		.173 (4.74)	
MOS 11H	.401 (6.67)		.394 (6.56)	
MOS 11M	.517 (3.09)		.495 (2.96)	
ACOL ($1,000)		.062 (2.61)		.060 (2.25)
Unemployment Rate at Reenlistment		−.171 (7.32)		−.169 (7.24)
Pay-grade Difference		.357 (8.09)		.349 (7.74)
Log-Likelihood	−9,770.96		−9,770.48	
Sample Size	10,000		10,000	

Table 6.14
Estimated Coefficients in Bivariate Probit Model for First-Term Survival and Reenlistment, Sample of Four-Year Obligors

Variable	Survive	Reenlist	Survive	Reenlist
ρ	0		−.060	
			(.29)	
Intercept	−.334	−.991	−.334	−.924
	(1.49)	(2.24)	(1.49)	(1.84)
Black	.047	.562	.047	.561
	(1.36)	(10.82)	(1.35)	(10.77)
Hispanic	.278	.099	.278	.114
	(4.21)	(1.25)	(4.10)	(1.26)
Married at Accession	−.222		−.222	
	(5.30)		(5.31)	
Dependents at Reenlistment		.188		.184
		(10.60)		(9.44)
High School Graduate	.493	−.067	.493	−.029
	(8.58)	(.64)	(8.59)	(.26)
Mental Group I–IIIA	.071	−.177	.071	−.174
	(2.39)	(4.10)	(2.39)	(4.00)
Waiver to Enlist	−.167		−.168	
	(3.57)		(3.58)	
Months in DEP	.034		.032	
	(7.49)		(7.48)	
Educational Benefits ($1,000)	−.003	.13	−.002	.012
	(.66)	(1.42)	(.65)	(1.39)
Unemployment at Accession	−.021	−.017	−.021	−.018
	(3.05)	(1.70)	(2.99)	(1.90)
Relative Military Pay at Accession	.356	−.295	.356	−.252
	(1.55)	(.88)	(1.55)	(.74)
Age >19 at Accession		−.001		.002
		(.03)		(.04)
FY Entry Qtr 1	.032		.032	
	(.82)		(.84)	
FY Entry Qtr 2	.005		−.004	
	(.15)		(.13)	
FY Entry Qtr 3	−.090		−.089	
	(2.58)		(2.56)	
MOS 11C	.116		.115	
	(3.25)		(3.22)	
MOS 11H	.287		.285	
	(5.57)		(5.54)	
MOS 11M	.466		.466	
	(3.75)		(3.76)	
ACOL ($1,000)		.078		.077
		(3.07)		(3.01)
Unemployment Rate at Reenlistment		.035		.035
		(1.64)		(1.64)
Pay-grade Difference		.281		.279
		(7.65)		(7.54)
Log-Likelihood	−10,237.70		−10,237.10	
Sample Size	10,000		10,000	

rich set of observable variables in our regressor vectors. In a context of sparser regressor vectors, allowance for nonzero ρ might become more important. Second, our assumption of bivariate normality implicitly imposes a linear relationship between ε_{it} and η_{it}. As Charles Brown's paper in this volume suggests, the relationship among unobserved propensities to stay in the Army may be considerably more complex. One possible approach in future research would be nonparametric estimation of the bivariate distribution of unobserved heterogeneity.[18]

V. Summary and Discussion

This study has used probit, logit, and proportional hazard models to analyze first-term attrition and reenlistment in the U.S. Army. Our substantive results include findings that high school graduates are much more likely to survive the first term but less likely to reenlist, minorities are more likely to survive and to reenlist, and reenlistment decisions are responsive to the pecuniary attractiveness of Army versus civilian employment.

One methodological finding is that, because of nonmonotonicity in the temporal pattern of attrition, some popular varieties of duration models are ill-suited for analyzing first-term survival. We also have explored the issue of dynamic selection effects. We have found that, once conditions at the time of reenlistment are controlled for, conditions at the time of initial enlistment that increase the supply of enlistees have a perverse effect on subsequent reenlistment decisions. For example, enlistees drawn into the Army by depressed civilian labor market conditions are less likely to reenlist later when the civilian market returns to normal. In estimating a joint model of attrition and reenlistment, we have found that our results are hardly affected by allowing for correlation of unobserved heterogeneity between the two processes. This suggests that the usual practice of ignoring the attrition process when estimating reenlistment models may not produce serious biases. This result might not hold, however, in situations with sparser sets of observed explanatory variables or if more flexible models of heterogeneity were introduced.

Acknowledgments

The authors thank Charles Brown, D. Alton Smith, and David Wise for their comments and Michael Baker for research assistance.

Notes

1. The many studies in these areas are too numerous to cite here. For literature reviews, see Nelson (1986) on enlistment supply, Buddin (1984, 1988) on attrition, and Roll and Warner (1986) on reenlistment.

2. An exception is the study by Antel, Hosek, and Peterson (1987), which does address this issue.

3. See Hogan, Smith, and Sylwester (1990) for a similar formulation.

4. Baldwin and Daula (1985a) previously used proportional hazard models to analyze attrition from the Army.

5. We have excluded 1,380 two-year obligors because of their small number and because most enlisted after 1980. We have also excluded recruits over age 25, who are likely to have prior service.

6. In 1977 the GI Bill was replaced with the Veteran's Educational Assistance Program (VEAP), a system with considerably lower benefits which required service member contributions as well. An experiment with higher benefits in 1980–81 grew into the Army College Fund (ACF) in 1982 and beyond. The ACF is targeted toward high-quality enlistees in CMF 11 and several other critical occupational areas.

7. An additional reason for the low percentages in mental groups I–IIIA is the misnorming of the test battery that generated the AFQT scores. As a result of this misnorming, recruiters in 1979–80 thought they were enlisting higher ability recruits than they actually were. The test score data used in this study are correctly normed.

8. The educational benefits averages after 1980 are somewhat misleading. Much higher Army College Fund benefits were made available to high-quality enlistees than to low-quality enlistees. Our educational benefits variable ranges from $1,570 to $6,950 for 1983 enlistees but only $1,900 to $4,070 for 1980 enlistees.

9. For the purposes of this paper an individual is considered a survivor if he stayed to within six months of completion of his enlistment. Losses mount in the last six months of enlistment contracts and for the most part represent voluntary releases to permit individuals to do such things as return to school.

10. We have performed the "reduced-form" experiment of removing the personal quality indicators from the model and reestimating the effects of the economic variables. Most of the estimates do not change much, but the estimated effect of relative pay becomes large and significantly positive.

11. The influence of better recruiting might, however, show up along other dimensions of enlistee performance. One of these is the enlistee's eligibility for reenlistment. See the discussion below.

12. The heterogeneity parameter Θ could not be estimated jointly with other parameters. The maximum likelihood value of Θ was obtained by a grid search procedure. As a result, standard error estimates for the estimated Θ were not obtained, but hypotheses about Θ were still testable by likelihood ratio methods.

13. Although their overall reenlistment rate is much higher than that of whites, blacks were found to be slightly less likely to be eligible to reenlist.

14. Higher unemployment at accession is also significantly negatively related to the probability of reenlistment eligibility.

15. See, for example, Lancaster (1979) and Heckman and Singer (1984).

16. See, for example, Gotz and McCall (1984) and Black, Hogan, and Sylwester (1987). Antel, Hosek, and Peterson (1987) previously have addressed this issue in the context of initial enlistment and attrition.

17. See Olsen (1980), for example.

18. For an example in a different context, see Card and Sullivan (1988).

Comment

David A. Wise

The goal of this paper is to estimate attrition and reenlistment jointly. The motivation for joint estimation is that parameter estimates in a reenlistment equation may be biased if the correction is not made for attrition. In particular, it may be that the disturbance term in the enlistment equation is correlated with attrition. The paper presents a straightforward model to make such a correction.

As it turns out, the correction for attrition has virtually no effect on the reenlistment parameters. Presumably this will be reassuring to previous researchers in this area. Nonetheless, the paper yields many interesting results. For example, there is a very strong relationship between attrition and whether the enlistee has a high school degree. The relationship between attrition and MOS specialty is also striking. Holding other personal attributes constant, blacks are considerably more likely than whites to reenlist. Relative performance in the military also seems to matter a good deal. Many of these results support earlier findings.

I have several comments on the paper, most of which pertain to the exposition of results. First, it seems to me unnecessary to present both probit and logit estimates; they are virtually identical. One would only expect them to differ if typical probabilities under consideration were very small.

Second, the ACOL variable should be explained briefly in the paper. The authors refer the reader to explanations presented in other project reports. But the variable plays a key role in the analysis; several of the other variables that are included make little sense if the reader does not understand what the ACOL variable is supposed to capture. In addition, the analysis would be more complete if this variable were included in the attrition equation, as well as the reenlistment equation.

Third, some enlistees are not eligible to reenlist. Based on reasonable judgment, the authors have chosen not to distinguish eligible from ineligible soldiers in the reenlistment equation. It

wasn't clear to me whether this was or was not the best way to proceed. It did occur to me, however, that the authors could easily have added a third equation to their model, estimating a relationship between reenlistment and eligibility similar to the relationship between reenlistment and attrition that they have already incorporated in the analysis. In fact, Charlie Brown did this in his analysis. Based on estimates by David Smith and Paul Hogan, it appears that if such a correction were made by Warner and Solon it probably would not change their results appreciably.

Fourth, I would like to see a more compelling explanation of the results. As presented, the paper does not make as much of the results as it could. It ends on a rather flat note and leaves the reader wishing for more. I believe that this problem could be solved by presenting a few simulations to highlight the potential importance of the results. For example, given enlistment and the personal attributes of the enlistees, the military can control the military pay component of the ACOL variable, educational benefits, paygrade differences, and, presumably, reenlistment eligibility. Suppose that the military would like to induce more high-quality enlistees to reenlist. One might simulate, based on the estimates now in the paper, how much pay would have to increase to achieve a given increase in reenlistment of high-quality enlistees. Of course, one might also have to consider how much reenlistment eligibility criteria would have to be changed to achieve the same overall manpower levels. A similar analysis could be conducted with respect to educational benefits. Similar questions could be addressed with respect to the differential attrition by MOS specialty. If one wanted to change that result, how much would pay have to change by specialty? These are only examples; the idea is to present some results that will give some punch to the estimates that the paper now presents and allow the reader to understand the implications of the analysis that has been done.

This may require the authors to give further consideration to the goals of their analysis. What did they intend the results to be used for when the analysis was undertaken?

Finally, I have a general comment that I presume the authors cannot do much about, at least in the short run. The analysis would be more complete, and more useful, if it were somehow tied to an enlistment equation. The importance of enlistment becomes evident when considering simulations like those mentioned above. Changes in pay, for example, would presumably affect enlistment as well as attrition and reenlistment. With enlistment, attrition, and reenlistment considered jointly, one would have a much more complete picture of the potential effects of changes in pay and other policies on military manpower.

In short, the paper is well done and clearly written. But I think that its value could be increased substantially by a more powerful exposition of the potential implications of the results.

7

Partial Careers: Civilian Earnings and the Optimal Duration of an Army Career

Frank P. Stafford

This paper provides a conceptual framework for studying military careers and uses a special merger of detailed Army records with Internal Revenue Service (IRS) and Social Security Administration (SSA) earnings records to examine the post-service labor market experience of U.S. Army "alumni." It is found that military occupational specialty, years of military and civilian experience, speed of promotion, race, and the state unemployment rate have an influence on earnings. The results imply that the optimal Army pay policy needs to be targeted to military occupational specialty: otherwise recruits may acquire training but provide an insufficient return to the Army. Specifically, Army pay policy needs to be shaped to achieve a partial career of optimal duration for recruits in different specialties.

An important component of the economic benefit to military service is improved post-service earnings in the civilian labor force. This fact, combined with a commitment to having a relatively youthful force, creates a special set of requirements for an optimal compensation and training policy

for the U.S. Army. Rather than being an employer with an interest in retaining employees for most of their work life, the Army is an employer with an interest in shaping a training and compensation policy to induce an optimal duration of military career that should commonly last for only a part of the person's work life, but for sufficient duration to recoup the investment in training costs and to contribute to Army objectives. In this paper the attachment of a person to a particular employer for only a portion of the work life is referred to as a partial career. The concept is related to that of "stepping stones" (Borjas and Rosen, 1980), but emphasizes the duration and nature of the attachment rather than the simple incidence.

One can imagine private-sector employers with a similar objective. For example, law firms often attract new graduates by a combination of salary and opportunities to acquire on-the-job training and expect these "recruits" to turn over. At some point it is rational for these people to switch to another employer who will pay for their previously acquired skills, and it is this subsequent payment which in part motivates their acceptance of the initial employer's offer. Other examples include new faculty at research universities or teaching fellows who accept employment in return for both current compensation and enhanced future compensation that will often be paid by a subsequent employer.

Individuals who opt to become CPAs or medical doctors pursue highly structured partial careers because, in addition to the training provided, there are no other ways to become certified. As those wishing to become mechanics or other types of military specialists can often get training outside the Army, is an attraction of an Army partial career a function of imperfections in the capital market? That is, by entering an explicit enlistment contract a recruit can do something in the Army that may not be replicated in civilian labor markets: he can receive a compensation stream initially above his productivity level and can later "repay" this with a subsequent excess of productivity over pay. This is true even if the skills are general, in the sense that numerous non-Army employers can make use of them.

The pay and training aspects of enlistment contracts are modeled formally by a partial careers model. The idea is that

when the enlistee signs up, the Army and the enlistee are committing to a time path of several variables: pay, training, and output to the Army. How these variables should be set for an optimum is a function of different Army and civilian occupations. First, it is unlikely that the optimum will involve a temporally coincident path of pay and productivity. Second, in some occupations there will be a larger payoff to the skill in the civilian labor market, making skill acquisition in the Army and post-Army benefits a larger share of the attraction of enlisting. It is not presumed that Army policy is fully consistent with such optimizing. Rather, a model of the sort outlined in this paper could provide a minimum cost benchmark against which to evaluate the current system and is consistent with the ACOL type of model used in simulating the effects of Army retention policy (Baldwin and Daula, 1985b).

One special reason why a "partial career" is widely optimal for many military occupations is that the value of service depends on the ability to mobilize the existing force to diverse and demanding locations, placing a special value on the physical condition of the force. Since this latter characteristic is generally age-specific, there is much more interest in partial careers by the Army. On the other hand what the Army should seek to avoid are dropouts and quitters, both of which absorb training resources and compensation that have a greater present value than the stream of services they provide. Dropouts are those recruits who turn out to perform below expectations and quitters are those recruits who meet or exceed expectations, but who fail to reenlist under the existing compensation regime.

Some of the critical information needed to implement a partial careers model includes the post-military earnings of the alumni in different Military Occupational Specialties (MOSs) as a result of differing years of service in those specialties, the value to the Army of those with different years of experience in particular MOSs, civilian earnings absent military service, and Army compensation for additional years of service by MOS. As an econometric and policy implementation problem, one of the difficulties is that of observing person-specific values of both civilian alternatives and value to the service.

I. A Model of Optimal Career Duration in the Army

The basic ingredient in this model is the idea of separate segments in a person's labor market career. Although those who separate sometimes reenlist, here we assume a maximum of two segments: an initial Army segment followed by a single civilian segment. The features of the Army segment are set out between the enlistee and the service in an initial enlistment contract. Therefore, this is a model in which the Army career is characterized as fulfilling a contract made under perfect foresight. The parties to the contract are assumed to have chosen the "right" contract in the sense that optimally arranged contracts in another specialized field would yield lower net benefits to the individual conditional on a given level of net return to the Army.

The skills developed in the Army have a financial payoff to the individual both as a consequence of Army compensation policy *and* as a consequence of future earnings power in the labor market. While in the Army the individual's utility function per unit time is

$$U_A = A(m_1) \tag{1}$$

where m_1 is market goods allocated to consumption while in the Army. In civilian life utility is a function of market goods per unit time

$$U_C = C(m_2) \tag{2}$$

where m_2 is market goods allocated to consumption while in civilian life. By having (1) and (2) as separate functions, we can easily allow for a preference or aversion to military service. As well, one can represent a payoff to immediacy or deferment of consumption to the civilian segment, depending on the specifics of (1) and (2). By separate equations for (1) and (2) we do not really mean the person's preferences differ in the two environments, but rather that the opportunities for consumption differ and that service or civilian life itself can be valued more highly by the individual. The individual's objective is to maximize the sum of the integrals of consumption in the Army and civilian life.

Skills, K, are developed in the Army over the interval $t_0 < t < t_1^-$ by

$$\dot{K} = a(s,K) - dK \tag{3}$$

where s ($0 <= s \leq 1$) is the fraction of time devoted to skill acquisition while in the Army, d is a depreciation parameter ($0<d<1$), and a (.) is a production function for skill acquisition in which acquiring skills in the Army occurs at the instantaneous cost of forgone Army output. The individual starts in the Army at t_0, and t_i is the time just prior to departure. In this model there is simply a training and earning decision with no leisure choice. This may be more realistic for people in their early careers since the largest increase in lifecycle leisure appears to be related to labor force retirements. During the Army interval financial assets, R, accrue according to

$$\dot{R} = (1-s)\,\alpha\,K - m_1 p_1 \tag{4}$$

where α is the rate of compensation per unit of Army service provided by the individual. While an Army policy variable, it is also a parameter for the individual. The time path of financial disbursement is not given special attention in this representation. An alternative specification could be to allow a simple form of time dependence to α, making it $\alpha(t)$, a time-varying parameter for the individual. A related modeling issue is raised by the work of Lazear (1981), which emphasized the potential multiplicity of compensation paths in forming a contract to elicit work effort through time. Time dependence allows one to consider the payoff to a time-sequenced payment for services in terms of retaining certain kinds of recruits.

In the civilian labor market the individual's skills are developed over the interval $t_1^+ < t < t_f$ according to

$$\dot{K} = c\,(s,K) - dK \tag{5}$$

where t_1^+ is the time just subsequent to leaving the Army and t_f is the end of labor market activity. Retirement behavior is not analyzed here. In civilian life financial assets accrue according to

$$\dot{R} = (1-s)\,\gamma\,K - m_2\,p_2 \tag{6}$$

where m_2 is market goods purchased in civilian life and p_2 is the price. At the point of departure from the Army there is a cost, c, which for simplicity we can represent as a monetary cost of moving to a new environment. In actuality it may be a period

of job transition during which labor market earnings are forfeited. We thus have

(7) $$R(t_1^-) - R(t_1^+) - c = 0$$

Defining

(8) $$\Phi = v[R(t_1^-) - R(t_1^+) - c]$$

(9) $$H_1 = A(m_1) + \lambda_R[(1-s)\alpha K - m_1 p_1] + \lambda_K[a(s,K) - dK]$$

(10) $$H_2 = C(m_2) + \lambda_R[(1-s)\gamma K - m_2 p_2] + \lambda_K[c(s,K) - dK],$$

necessary conditions for an optimum include (3)–(6) and

(11) $$\dot{\lambda}_R = -\partial H_1/\partial R = -\partial H_2/\partial R = 0; \quad t_0 < t < t_f,$$

$$\dot{\lambda}_K = -\partial H_1/\partial K = -\partial H_2/\partial K$$

or $$\dot{\lambda}_K = \lambda_R\,\alpha(s-1) + \lambda_K[d - a_k]; \quad t_0 < t < t_1^-$$

(12) $$\dot{\lambda}_K = \lambda_R\,\gamma(s-1) + \lambda_K[d - c_K]; \quad t_1^+ < t < t_f$$

$$\lambda_{Kt1^-} = \lambda_{Kt1^+}$$

$$\lambda_{Ktf} = 0$$

and

(13) $$\partial\Phi/\partial R(t_1^-) = v = \lambda_R(t_1^-); \quad \partial\Phi/\partial R(t_1^+) = v = \lambda_R(t_1^+)$$

(14) $$H_1(t_1^-) - H_2(t_1^+) = 0$$

(15) $$\partial H_1/\partial m_1 = 0; \quad A_{m1} = \lambda_R\, p_1$$

(16) $$\partial H_1/\partial s = 0; \quad -\lambda_R\,\alpha K + \lambda_K\, a_s = 0; \quad \lambda_k a_s = \lambda_R\,\alpha K$$

(17) $$\partial H_2/\partial m_2 = 0; \quad C_{m2} = \lambda_R\, p_2$$

(18) $$\partial H_2/\partial s = 0; \quad -\lambda_R\,\gamma K + \lambda_K\, C_s = 0; \quad \lambda_K\, c_s = \lambda_R\,\gamma K$$

While full solution of this model is not achievable without more specialization of the functional forms, we can infer several likely features of a path satisfying these necessary conditions for an optimum, and these features appear to be informative for compensation policy. If an individual is compensated for effort in the Army devoted to producing output (α "high"), then there will be incentives to reduce effort devoted to future-

oriented acquisition of skills to be used after separation, as is suggested by (16). On the other hand, if the future civilian employment will richly reward Army acquired skills (γ"high"), implying a high value to λ_K while in the Army, then there will be individual incentive to "shirk." Rather than producing output while in service, effort will go toward producing skills for future use. A contract with higher pay while in the Army combined with smaller opportunities for training to realize post-Army benefits of equal utility value to the individual could be in the Army's interest in such a case.

Another way of seeing this incentive problem from (16) is to note that large civilian labor market payoffs will act to increase the value of λ_K, and unless the Army increases the immediate payoff to production by increasing α, there will be incentives to leave or train for the post-Army career.[1] In our empirical section we see that a measure of acquired skill, rapid promotion through pay grades (which seems to be concentrated in the MOSs with good external opportunities), is well rewarded in the external market. Since the pay scale in the Army provides only small increases in pay for higher pay grades, not only would there be incentives to leave for these civilian opportunities (as implied by (14), since better within-Army pay will extend the time segment in the Army during which the optimized value of H_1 can be as high as the optimized value of H_2), but there would be incentives to seek out Army contracts and assignments that lead to a better civilian career rather than to expend effort toward Army objectives.

Different military occupational specialties have differing payoffs in the civilian labor market. An MOS which has a low civilian return in terms of payment for civilian output (γ low) may lead to more production of output while in the Army. This would be a military-specific MOS, and without some appropriate compensation for acquisition of skills while in service, there can be insufficient incentives to acquire such skills or serve at all. Here the appropriate policy would seem to be a higher level of α as well as a possibly rising path for α. The compensation for such an occupation could be leveled off or reduced to elicit exit of workers experienced beyond some point.

II. Studying Army Compensation Based on the Model

In this section we will outline the use of data files for an empirical examination of the nature of Army compensation as it relates to civilian earnings. Special attention is given to obtaining data for different military occupations to see whether the compensation seems to be consistent with some of the themes suggested by our model. The discussion will focus on three issues:

1. To the extent that military experience represents a form of human capital that can be used in the civilian labor market, one force attracting recruits is *future* or post-Army compensation of Army-acquired skills. Greater future compensation would add to λ_K during the Army career. The dilemma this presents for the Army is that the skill-building dimension is both an initial positive attraction and a force that creates incentives to leave possibly too early, and to seek out skill acquisition beyond that in the enlistment contract rather than produce Army output while in the service. Does skill-building, as measured by rapid promotion or by years of military experience, get rewarded in the external market more highly than in the Army? If so, the Army could become a "revolving door," providing a great deal of valuable training for the civilian labor force but itself getting little payoff per enlistee.

2. Does the post-Army earnings experience of alumni in *different military specialties* conform to expectations one might have about the extent to which the Army skills of the specialties are specific to military activities? This is important since, if true, the policy implication is to treat people in different specialties with significantly different compensation programs.

3. Does the Army policy target higher compensation to those in specialties with higher civilian earnings? If not, one would expect "excessive" attrition of those with key specialties to the civilian market. Again, the issue here is one of the value of flexibility in compensation policy.

To study alumni earnings requires a merger of data from the Defense Manpower Data Center's (DMDC) Post-Service Earnings History File (PSEHF) and the Enlisted Panel Research Data Base (EPRDB). Other data sets such as the 1977 High School Graduate Panel have been used to estimate

post-service earnings functions (see Crane and Wise, 1987). The PSEHF has the advantages of tracking recent separatees and providing enough observations to examine earnings for more detailed occupational and demographic groups.

A key aspect of the data on post-Army earnings is that they are from IRS and Social Security and hence are grouped to preserve anonymity. When examining the estimates below, remember we are working with earnings, so few hours of market work can shape the value of the dependent variable. Ideally we would like the potential hourly wage rate rather than actual earnings, but hours of work is not available in this data base. In the basic data set, the PSEHF, there are several variables used to create or define the cells. These "cell" variables are: Branch of Service (1=Army), Years of Service, Education, Grade Level, Year of Separation from the Service (1972–80), and Military Occupation Category. This last variable is a highly aggregated occupational variable and is not adequate to go far in examining the post-service earnings of alumni with very particular specialties.

In addition to the "cell" variables there are variables that are cell averages: these variables were not used to define cells but are included in terms of their average values for each cell. The documentation refers to these as "carry-along" variables. The variables so defined include: Mean Age (at last entry and at last separation), Mean Education (at last separation), Percent with Education < High School, Percent with Education = Some High School, Percent with Education = Some College, Percent with Education = College Graduate, and Percent with Education = Advanced Degree(s). For specific definitions of these and other variables, see Variable Description and Coding in Johnson (1983). In the PSEHF there are four samples: Officer-IRS, Officer-SSA, Enlisted-IRS, and Enlisted-SSA. The variables available in the four samples differ somewhat. In particular, the Military Occupation Categories differ as do the pay-grade variables. For this reason, as well as differences in Army and post-Army careers, it is best to keep the analysis of the groups separate. Our interest is in examining enlisted personnel, and most of the analysis is based on IRS earnings.

The list of variables in the PSEHF is not sufficient to get a good look at how different Army careers influence civilian earnings (as well as who chooses what type of Army career and who leaves the Army—more on this below). What was done was to add to the PSEHF a set of additional "carry-along" variables from the EPRDB. The first and most obvious of these "added carry-along" variables was the percent in additional military occupational specialties. To illustrate, for the cells defined by Enlisted-IRS Military Occupation Category Code 4 (which corresponds to Medical, Dental) there were appended a set of added carry-along variables that would be the percent of each cell that is composed of separatees from more detailed occupations, MOSs.

There are separate, detailed MOS codes for Enlisted and Officer groups. To give some idea of the details, these include 16E=Hawk fire control crewmember, 62F=crane operator, 42D=dental lab specialist, 51K=plumber, etc. For analyzing subsequent labor market earnings, there may be a payoff to having quite detailed MOS codes when there is a civilian occupation (such as plumber) but not for keeping some of the detail on military codes. Here a Hawk fire control crewmember need not be distinguished from a Hercules fire control crewmember, but these two and other similar occupations should be distinguished from an aggregation including Hawk and Hercules mechanics. Another possible drawback of excessive occupational detail might be the small and zero percent representation in some cells. What was done was to work with the detailed MOSs but to group together those that seemed to have *a priori* similarities. More on this below.

Work on post-service earnings by Borjas and Welch (1984) indicated that only a small percent of retirees did not get themselves settled into the labor market shortly after separation. Their sample consisted of more experienced (age 37 to 64) and a higher percent officer-level personnel. Because the sample studied in the current project was younger and less skilled, there was more concern over the issue of dealing with the transition time from separation. A very short time will lead to the inclusion of temporary or "frictional" lack of employment and earnings, but too long a time interval may incorrectly obscure labor market transition costs which, worse yet, may be concentrated in selected MOSs. Fortunately, year of separation is one of the cell vari-

ables, and in some of the analysis this issue was dealt with by specifying dummy variables for whether first year out and whether second year out.

Supplementary variables from the EPRDB included as additional carry-along variables were marital status, MOS, and home state. The purpose of the special merged file, then, was to estimate the post-service earnings of enlisted Army alumni as a function of

1. Personal characteristics (education, marital status, AFQT, race, ...).

2. Military experience (years of service, MOS specialties, years of service × MOS specialties, pay grade, market position of their specialty, enlistment bonus, reason for separation, waiver code).

3. Unobserved characteristics.

In analyzing the effect of military experience on earnings it is essential to control for pre-entry personal characteristics. This is because, consistent with the model of partial careers, individuals and the Army select a contract based on the enlistee's characteristics. If more able people are recruited for military occupations with higher civilian pay, the absence of personal characteristics would bias upward the apparent influence of Army experience on civilian earnings.

Starting with the first two sets of variables, one can think of a simple regression for the enlisted sample of cell mean IRS earnings[2] on mean or percent variables, beginning with years since separation (defined as the difference between year of earnings and year of separation with possible dummies for first year out), race/sex (female, black male, nonblack male), education/grade level (enlisted–less than high school graduate grade E6 and below, enlisted–less than high school graduate grade E7 and above, etc.), year of service category, and broad Military Occupation Category. As well, there were carry-along variables such as mean age, percent frequency distribution by pay grade, GI Bill data fields (average allotment received by recipients and percent receiving any), and year of entry (mean). Also, there were the added carry-along variables, the most important of which were the yet-to-be-defined detailed MOS percentages. In addition there were other carry-along variables such as AFQT means or AFQT groups.

The estimated earnings equation would suffer from several obvious problems, including the fact that there is not a clear delineation between personal and military experience variables. Receipt of an enlistment bonus could be thought of as both a personal skill variable *and* a mechanism by which the Army can create loyalty or an "efficiency wage" to elicit extra effort for future evaluation. Another problem is that those who leave at various points will differ in terms of unobserved (personal) characteristics.

To make some allowance for unobserved characteristics, the following strategy was considered but not implemented: estimate a separation (S) probit which is a function of variables that affect civilian (and possibly military) earnings (X) and of variables which affect only military earnings or tastes $A(m_1)$ for the military (Z). From this probit one could calculate λ_1 and could take the average value of λ_1 for each of the cells in the previous earnings equations. What variables are candidates for the Z-vector? This was the weak link in the approach. One possibility would be the state unemployment rate from the year of enlistment. The more "loyal" sign up from tight labor markets, but after Army experience they can be employed in any one of several geographic areas. As reported below, the influence of state unemployment on civilian earnings is not particularly strong, suggesting that the payoff to its use in a sample selection correction would be minor as well.

Uses of the resulting earnings equation by detailed MOS and other characteristics could be to develop a stylized empirical implementation of the optimal duration of a military career, including simulation with the ACOL model, which estimates the cost of leaving in terms of projected civilian earnings from a given point on in comparison with Army earnings from a given point on (Smith, Sylwester, and Villa, 1990). If we know how additional years of service are rewarded in the Army and how they contribute to altered paths of a subsequent post-Army career, then it should be possible to calculate the optimal switch point out of military service, by MOS, from the perspective of the individual. It should also be possible to stylize an Army productivity path (net of instruction cost). The question then becomes, What is the optimal duration of an Army career by MOS from the perspective of the Army, and what compensation

path (or paths) would accomplish an Army career of optimal duration at smaller total outlays per value of service supplied?

III. Empirical Findings

Here we use the merged data base described in Section II for a preliminary examination of civilian earnings patterns. Included as Table 7.1 are two OLS earnings equations, differing in the way in which Military Occupational Category (MOC) is or is not interacted with months since separation from the Army. The dependent variable is unlogged SSA earnings. Independent variables include race, sex, years of service categories, high school graduate, E7, Military Occupational Category (Combat, Electronics/Communications, Electrical/Mechanic/Craftsman, Medical/Dental, Support/Administration, Other), months since separation and its square, interactions of the months variables with MOCs (second regression), mean AFQT, mean age at last separation, percent in four categories of dependents, and mean pay grade.

The first main point is that the results are, by and large, reasonable. The adjusted R^2 is about .27 and the coefficients make sense, particularly the comparison between equations (1) and (2). The differential for female seems larger than the magnitude reported in other studies of civilian earnings, but this may reflect separation from the service for childbirth. It is for this reason that we subsequently examine the role of dependents as an indicator of childbearing for women alumni. Service year variables generally indicate worse earnings for more years of service, particularly in the beyond-twenty-years groups. Here the military pensions may be inducing a labor supply effect. Also, with pay grade in the equation, longer years of service may be regarded as measures of how *slowly* a person has progressed through the pay scale. Subsequent specifications address the issue of military experience and civilian earnings. Military pay grade is strongly related to civilian earnings, which can be taken as evidence on question three above. In particular one can interpret the strong pay grade effect to mean that the compensation system inside the service is at least partly effective in matching opportunity costs in the civilian sector. This is the subject of additional analysis below.

Table 7.1
Social Security Earnings of Army Alumni, 1981

	(1)		(2)	
Variable	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
Female	–3740.2	308.7	–3722.2	312.3
Black Male	–385.0	145.5	–379.3	145.5
Service Year				
5	–331.6	328.0	–278.8	328.5
6,7	–500.2	380.5	–415.3	381.4
8,9	–120.7	458.7	2.6	461.0
10,11	–200.0	519.6	–69.3	521.8
12,13	–753.1	572.5	–600.1	574.9
14,15	–113.5	642.9	35.9	645.0
16,17	820.5	713.5	–648.3	715.7
18–20	–596.1	784.1	–448.2	785.6
21	–89.4	833.0	85.3	835.9
22	–447.8	885.3	–257.1	888.8
23	–689.4	927.0	–493.4	930.6
24,25	–222.9	969.9	–38.3	973.2
26,27	–1129.4	1048.2	–909.6	1052.4
28–30	–1075.2	1125.3	–830.4	1130.2
31+	–1810.7	1232.8	–1535.3	1238.7
High School	743.7	147.8	738.2	147.9
Mean Pay Grade	11.2	1.8	10.2	1.9
Pct. E7 or >	507.8	337.0	655.9	345.0
Months Out (Mo)	13.6	15.4	–36.5	36.6
Months Out^2	.13	.09	.47	.21
Mean AFQT	10.8	4.6	12.1	4.6
Mean Age	–171.0	35.7	–170.4	35.8
Dependents				
Pct. 1	13.1	5.4	13.1	5.4
Pct. 2	14.2	5.5	14.0	5.6
Pct. 3	10.9	5.1	10.8	5.2
Pct. 4 >	20.0	4.6	19.9	4.7

Table 7.1 (continued)

	(1)		(2)	
Variable	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
Occupation				
Commun	204.8	196.1	−2011.7	2047.6
Craft	339.6	197.0	−2283.5	2073.5
Admin	−208.5	184.2	−1897.5	1920.8
Med/Dent	−121.1	208.4	−381.6	2150.1
Other	497.5	332.5	−1032.6	3485.2
Commun × Mo	—	—	77.1	50.9
Commun × Mo^2	—	—	−.54	.29
Crft × Mo	—	—	82.7	51.5
Crft × Mo^2	—	—	−.55	.30
Adm × Mo	—	—	64.5	47.7
Adm × Mo^2	—	—	−.47	.28
Med × Mo	—	—	6.2	53.5
Med × Mo^2	—	—	−.03	.31
Oth × Mo	—	—	31.7	90.4
Oth × Mo^2	—	—	−.15	.54
Constant	6837.1	1272.0	8623.1	1878.5
Adjusted R^2	.267		.269	
Sample Size	2917		2917	

The MOCs are specified as differences from the excluded combat group. Where the MOCs are interacted with months of post-service experience (Mo), one observes a quite pronounced initial rise in civilian earnings (at a rate of about $1,000 per year, cross-sectionally) for electronics, electrician/craftsmen, and a bit lower for supply and administration, and lower still for medical/dental and other. The fact that the post-service profiles vary quite a lot in shape suggests that some military specialties are valuable because they lead to acquisition of on-the-job training after leaving the military (λ_K high). This can be thought of as a form of deferred compensation that motivates enlistment but, as noted above,

can encourage exit to the civilian labor force and a loss of return to the Army if this occurs "too early" in the partial career.

The percent dependents in various categories has a weak relation to earnings. In some of the disaggregated equations below there is a substantial effect of dependents (Tables 7.2 and 7.4 below, where those with more dependents earn more in the civilian market). It is possible to believe that the generally weak effect of dependents on civilian earnings occurs because a sufficient number of the variables with which number of dependents is correlated are included in the equation so as to reduce the apparent effect of dependents. Possibly this implies that a large allowance for dependents is less sensible: those with more dependents do not have dramatically better civilian opportunities but have associated costs to the Army in terms of retention and are less valuable from the perspective of global mobility.

Would deletion of pay grade from these initial equations lead one to observe a pattern for the differing effect of years of military service on civilian earnings in differing military occupations like that reported recently (Goldberg and Warner, 1987)? Later results for our more complete model suggest this to be the case. This is reassuring since it suggests that the basic pattern they observed for the 1972–77 period also applies for these later data (and for the Army). For the purpose of this study, the results in Table 7.1 are encouraging because they support the idea that there are substantially different training and earnings trajectories for different technical specialties. This is more apparent from examination of earnings for detailed occupations, namely the MOSs.

Because IRS data were available for more years, most of the subsequent work was done with IRS data. The second set of estimates, Table 7.2, is a very basic model applied to the three broad occupational groups separately. The natural logarithm of 1980 IRS earnings was used as the dependent variable (conditional on earnings being greater than zero). Earnings were taken for 1980 rather than averaged over 1979–1983, since the latter would have required that the analysis be restricted to those who left service no later than 1981 or 1982 in order to obtain an observation on 1983 earnings.

Table 7.2
Ln IRS Earnings of Army Alumni, 1980

COMBAT		
Variable	**Coefficient**	**Standard error**
Female	–.65	.21
Black Male	–.12	.04
Yrs Civexp	.063	.008
Yrs Milexp	–.002	.003
Mean AFQT/100	.100	.147
Mean Ed (Last Sep)	.069	.018
Pct w/Deps/100	.386	.111
Constant	7.732	.206
Adjusted R^2	.178	
Sample Size	513	
MECHANICS/CRAFTSMEN		
Variable	**Coefficient**	**Standard error**
Female	–.48	.14
Black Male	.05	.04
Yrs Civexp	.053	.046
Yrs Milexp	–.002	.003
Mean AFQT/100	.632	.159
Mean Ed (Last Sep)	.027	.019
Pct w/Deps/100	.507	.132
Constant	7.771	.230
Adjusted R^2	.187	
Sample Size	495	
ADMINISTRATION		
Variable	**Coefficient**	**Standard error**
Female	–.34	.07
Black Male	–.07	.03
Yrs Civexp	.063	.006
Yrs Milexp	–.001	.002
Mean AFQT/100	5.583	1.245
Mean Ed (Last Sep)	.056	.012
Pct w/Deps/100	.404	.086
Constant	7.783	.160
Adjusted R^2	.282	
Sample Size	681	

The main result is that earnings increase at a rate of 5 to 6 percent with additional years of civilian labor market experience. Since the mean of civilian experience is about six years, this implies a healthy post-service earnings growth, at least for the relatively early years after service. Years of military experience have no apparent relationship to earnings. This is slightly surprising. In the first tables it seemed likely that military pay grade was responsible for the apparent negative effect of longer military careers. The paradox here is that earnings grow rapidly for those coming out of the military, implying a substantial civilian labor market value to military experience. Yet longer duration military careers do not have large additional payoffs in terms of civilian earnings for any of the three occupational groupings. If this result were true (and later work suggests it is not), from the enlistee's perspective the optimal duration of a military career may be short unless (the present value of) military compensation itself rises sufficiently to make a permanent military career attractive. This is because additional years of military experience at least postpone the acquisition of additional and valuable civilian experience.

There are differences across the occupational groups. AFQT has an effect only for mechanics and craftsmen, and even there the effect is not great. For combat and administration, education has an effect of a magnitude similar to that reported in most earnings estimates; it is somewhat lower for mechanics and craftsmen. Unlike the results presented above, dependents (as measured by percent with one or more dependents) has a substantial effect on civilian earnings. Percent female has a larger negative effect on civilian earnings than reported in most studies of the civilian labor market, while percent black has a smaller effect. Indeed, percent black is positive, though not statistically significant for mechanics/craftsmen.

Examination of earnings for those in specific groupings of detailed MOSs answers the general question raised in the theoretical section: does the post-Army path of earnings differ sharply across different skills? If so, the model suggests a need for differences by specialty in the compensation path for the Army. In Table 7.3 are estimates of a model in which experience variables are interacted with the three MOS aggregates to look

Table 7.3
Ln IRS Earnings of Army Alumni, 1983

	(1)		(2)	
Variable	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
Female	–.44	.07	–.45	.08
Black Male	–.10	.06	–.13	.06
Service Year (SY)				
5	.138	.071	.181	.072
6,7	.092	.107	.163	.108
8,9	–.030	.179	.074	.181
High School	.280	.059	.356	.057
Months Out (Mo)	.015	.012	.012	.013
Months Out^2	.000079	.000120	–.000048	.000122
AFQT/100	–.159	.286	.107	.283
Avg. Pay Grade	.0019	.0005	—	—
Mean Age	.0059	.0124	.0022	.0127
Dependents				
Pct. 0	–.0067	.0058	–.0056	.0057
Pct. 1	–.0057	.0062	–.0025	.0063
Pct. 2	–.0086	.0059	–.0052	.0059
Pct. 3	–.0077	.0063	–.0042	.0064
Occupation				
Craft	–.027	.296	.012	.303
Crft × SY5	.073	.061	.053	.062
Crft × SY67	.082	.092	.056	.094
Crft × Mo	–.0014	.0122	–.0041	.0124
Crft × Mo^2	.000037	.000118	.000059	.000120
Mil × SY5	–.000665	.004000	–.000432	.004090
Mil × SY67	.01287	.00651	.00912	.00658
Mil × SY89	–.00821	.011165	–.01021	.01191
Mil × Mo	–.00021	.000923	.000143	.000940
Mil × Mo^2	.0000023	.0000093	–.0000021	.0000094
Sup × SY5	–.003410	.002480	–.00575	.00245
Sup × SY67	–.003290	.003140	–.00444	.00320
Sup × SY89	–.005260	.004200	–.00549	.00430
Sup × Mo	–.000756	–.000417	–.000654	.000426
Sup × Mo^2	.0000065	.0000038	.0000054	.0000040
% Milspecific	.00565	.02155	–.00201	.02196
%Non-mil Supmos	.02151	.01060	.01907	.01083
Constant	8.112	.686	8.666	.685
Adjusted R^2	.344		.313	
Sample Size	287		287	

at post-Army earnings differences by MOS specialties. The earnings equations are based on three separate aggregations of detailed MOSs into groups that *a priori* seemed to be similar in terms of military career. Specifically, these groups are Combat (mil), Craftsmen (crft) and Administration (sup).[3] The natural logarithm of 1983 IRS earnings was used as the dependent variable (conditional on earnings being greater than zero).

As with the earlier estimates, earnings increase at a substantial rate with additional time (measured in months in the regression) in the civilian labor market, at least for the relatively early years after service. Years of military experience have an increasing effect on post-military earnings for year 5 (.138) and then decline to a lower level for six to seven years of experience (.092) and then turn slightly negative for eight to nine years of experience (–.03). Service years 3–4 is the excluded category. What this suggests is that there may be selection, so that those with better civilian alternatives get out with seven or fewer years of experience or that while military experience improves civilian earnings, it does so only up to a point.

Other aspects of the regression include different paths of earnings as a function of MOS specialties. For example, (looking at point estimates only) those in supervisory MOSs get a smaller yet positive benefit from longer Army careers (service year 5 – service year 8–9 – Sup × SY5 – Sup × SY89, respectively) and tend to get a civilian labor force payoff longer after separating (Sup × Mo is slightly negative but Sup × Mo^2 is slightly positive). There is also evidence that a group of MOSs identified as "non-military specific supervisory" (% Non-Mil Supmos) returns slightly more to civilian alumni.

A detailed earnings function for a sample of separatees is presented in Table 7.3, column 2. It is the same interactive equation as presented in column 1 less the variable for military pay grade. A comparison of Table 7.3 columns 1 and 2 indicates that deletion of the pay-grade variable increases the estimated effect of years of military experience on post-military earnings. Specifically, the coefficients of separation in Service Year 5, Service Year 6–7 and Service Year 8–9 rise from .138, .092, and –.03 to .181, .164, and .074, respectively.

In both cases one can interpret the declining payoff to added years of military experience beyond Service Year 5 as some form of selective attrition based on variables not readily measurable in the merged data set. Note, however, that this selection problem appears sharply attenuated in comparison to regressions using the much larger file that does not include the "added carry-along" variables. The effect of experience can be seen to differ by MOS. In these equations we can see a qualitative pattern which one would expect *a priori*. We observe that the payoff to military experience is greatest for those in craft MOSs. (See the coefficients on Crft × SY5 and Crft × SY67.) While not in themselves significant, they are significantly larger than those on supervisory occupations (Sup × SY5 and Sup × SY67). Taken at the point estimate values we have a profile of .23 and .22 for those with 5 and 6–7 years, respectively, in craft MOSs and a profile of .17 and .16 for those in supervisory MOSs. In addition, the post-service earnings of those with supervisory MOSs grows more quickly after separation from the Army in comparison to those with post-military careers in craft MOSs.

The last set of earnings equations examines several issues raised to this point. First, is it possible that the large earnings differential between men and women alumni can be explained by the possibility that women may leave the Army for childbearing reasons? To examine this the variable % 0 dependents was defined for each cell. Women with children will have dependents,[4] and the earnings of women with no dependents should be used for examining the earnings of women alumni. Second, the transition period from military to civilian employment could extend beyond one year, so dummy variables for both one and two years out are included. Third, a more refined pay grade gap was defined.[5] The pay-grade by Military Occupational Category and years of service was defined as the expected pay grade for each cell. The pay-grade gap was defined as the average cell pay grade less this expectation measure. Fourth, the sample was restricted to those with 20 years of service or fewer to limit the influence that pension benefits could have on the labor supply of older alumni. Fifth, job market opportunities as influenced by the state unemployment rate were examined.

The notable aspects of this earnings equation in Table 7.4 are as follows:

1. Additional years of military experience add substantially to civilian earnings but at a decreasing rate.

2. Civilian experience continues to be more important than military experience. The interaction of civilian experience and military experience is negative, a result consistent with more rapid declines in the incentive for on-the-job training for older workers predicted by lifecycle investment models.

3. There continues to be substantial dispersion across the MOS aggregations in the magnitude of these and other results, suggesting that the better approach to military compensation involves "fine-tuning" by occupation.

4. The mean AFQT score by cell makes some difference for craftsmen and administrators but has a substantial impact only for the administrators.

5. Most of the earnings penalty appears to be within the first year out. The magnitude of the second-year-out coefficient is very close to zero and is even slightly positive for the administrators.

6. The payoff to education appears to be in line with results for the larger civilian-labor-market earnings literature, ranging from .043 per year for combat to .077 for administrators.

7. The effect of percent with no dependents is very small, just as in earlier formulations, suggesting that the opportunity cost in terms of civilian labor market options is not that different for those with dependents. A possible rationale for payments to those with dependents is that their utility from additional years of service is reduced, and hence, a premium is necessary if the Army wants to retain them.

8. A substantial differential exists between black and white men even though we have a fairly homogeneous group and a set of effective earnings predictors.

Table 7.4
Ln IRS Earnings of Army Alumni With Fewer Than 20 Years of Service, 1980

COMBAT

	(1)	
Variable	**Coefficient**	**Std. Error**
Female	–.50	.22
Black Male	–.12	.02
Military Exp	.035	.013
Mil Exp^2	–.00153	.00049
Civilian Exp	.058	.021
Civ Exp^2	–.00074	.00158
Civ Exp × Mil Exp	–.000309	.000612
AFQT/100	–.0761	.0936
Mean Ed Last Sep	.043	.009
First Year Out	–.159	.053
Second Year Out	–.028	.038
% 0 Dependents	–.051	.062
Fem × % 0 Dep	–.058	.317
Pay Grade Gap	.139	.016
Unemploy Rate	–.037	.006
Constant	8.789	.136
Adjusted R^2	.350	
Sample Size	1493	

MECHANICS/CRAFTSMEN

	(2)	
Variable	**Coefficient**	**Std. Error**
Female	–.86	.12
Black Male	–.06	.02
Military Exp	.065	.010
Mil Exp^2	–.00251	.00042
Civilian Exp	.092	.018
Civ Exp^2	–.00184	.00137
Civ Exp × Mil Exp	–.00267	.00053
AFQT/100	.252	.084
Mean Ed Last Sep	.051	.008
First Year Out	–.119	.045

Table 7.4 (continued)

MECHANICS/CRAFTSMEN

	(2)	
Variable	**Coefficient**	**Std. Error**
Second Year Out	–.018	.032
% 0 Dependents	–.122	.054
Fem × % 0 Dep	.647	.190
Pay Grade Gap	.131	.015
Unemploy Rate	–.033	.005
Constant	8.351	.122
Adjusted R^2	.468	
Sample Size	1430	

ADMINISTRATION

	(3)	
Variable	**Coefficient**	**Std. Error**
Female	–.38	.05
Black Male	–.14	.02
Military Exp	.067	.008
Mil Exp^2	–.0028	.0003
Civilian Exp	.084	.015
Civ Exp^2	–.0022	.0011
Civ Exp × Mil Exp	–.00063	.00042
AFQT/100	–.193	.069
Mean Ed Last Sep	.077	.006
First Year Out	–.085	.038
Second Year Out	.016	.027
% 0 Dependents	–.004	.043
Fem × % 0 Dep	.071	.080
Pay Grade Gap	.148	.010
Unemploy Rate	–.025	.004
Constant	8.139	.095
Adjusted R^2	.720	
Sample Size	1915	

An investigation of the influence of GI Bill allotments and participation percents indicates that there is not a strong relation between these GI Bill variables and civilian earnings. The initial specification was as a shift in earnings. Interactions were used to determine whether the influence of GI Bill payments is initially to depress civilian earnings via formal school-

ing and on-the-job training and then to accentuate earnings later in the civilian partial career. No consistent support was found for this prediction.

The influence of the more refined pay-grade gap variable seems intriguing. It is strong in terms of statistical significance and because a one-grade level increment beyond normal raises post-service earnings by around 15 percent. From an examination of the military pay table (Stafford, 1987), it can be seen that this increase is not far out of line with increases in monthly basic pay as grade rises. To illustrate, in October 1982 for enlisted personnel with 10 years of service, the average percentage increase in monthly pay for a higher pay grade was approximately 15 percent as well! What this suggests is that, as noted before, military compensation policy is either carefully or fortuitously targeted to "meet the civilian market."

An alternative interpretation is that unintended overpayment (underpayment) in the military will lead to an exit (retention) only when the person happens to land a civilian earnings opportunity that is sufficiently out (in) on the offer distribution to make an exit (retention) worthwhile. Another perspective, not supported by the estimate, is that the Army may go through great effort to assess the value of its service people, but if higher pay grade means only briefly higher Army earnings, there will be "excessive" exits to a civilian labor market that rewards this better performance more highly and persistently.[6]

IV. Conclusion

There appears to be a payoff from examination of earnings of Army alumni at the level of disaggregated occupational specialties. Only when an extensive set of variables is included in the analysis does one observe a reasonable influence of military experience on post-Army earnings. The evidence suggests different payoffs to military experience in terms of civilian alternatives. A concern is that without some fine-tuning of compensation policy the Army will overpay some in occupations where civilian earnings are not as attractive and will have an excessively long duration of the Army partial career. At the same time the pay will not be sufficiently high, nor rise through time sufficiently rapidly, to induce reenlist-

ment by those who have growth to Army productivity only after a substantial training period.

Those promoted more quickly were found to have better civilian pay alternatives, but these were not much different from the pay increments awarded in the pay table. Thus, concern over loss of the better reenlistment prospects seems unwarranted on this score. The civilian earnings of black men and particularly of women were observed to be lower than those of white men. Interpretation of the male-female difference is problematic given the lack of variables representing their childbearing status. The black-white difference seems more troubling, for it indicates that the civilian labor market pays less to black men even after statistical controls were applied for a long list of personal and work experience variables and for fairly narrowly defined occupational groups.

Separatees experience a cost in terms of an earnings penalty primarily within the first year out. The magnitude of the civilian earnings effect of percent with no dependents is very small in all earnings formulations, suggesting that the opportunity cost in terms of civilian labor market options is not that different for those with dependents.

Acknowledgments

I would like to thank Matthew Black, Tom Daula, Tom Hungerford, and Walter Oi for valuable comments on earlier drafts of this paper. Special thanks go to Charles Brown and D. Alton Smith for numerous research strategy suggestions, many of which turned out to be productive.

Notes

1. Larger values of λ_K will imply increasing levels of s to lower a_s. Larger values of α will lead to lower values of s.

2. To use the Social Security earnings, as in some of the reported regressions, required correction of the cell means for truncation at the earnings ceiling. These and other issues in working with the grouped earnings data are discussed in Brown (1988).

3. Note that these MOS aggregates are different from the combat, craftsmen, and administration MOCs in Table 7.2.

Only the interactions between mil and experience and between sup and experience were included, because of colinearity.

4. Those who are expecting children may also have low or no earnings, but would also be indicated to have zero dependents.

5. This specific form was suggested by D. Alton Smith.

6. What could happen is that good performers receive a higher pay grade, but the rate of future promotions is slowed down.

Comment

Walter Y. Oi

I. Steps, Stepping Stones, and a Taxonomy of Job Types

An employment relation, which is usually called a job, involves more than a simple exchange of money for labor time. It is a *composite bundle* described by, among other things, the tasks that have to be performed, the responsibilities that must be assumed, and the by-products—good or bad—that go along with the position. According to Doeringer and Piore (1971), an entry-level job in the primary labor market will ordinarily constitute the first step in a job ladder that will result in what R. E. Hall (1981) would call a "lifetime job." Other jobs in the secondary labor market—grape picker, night watchman, cashier at a fast-food restaurant—come closer to a one-dimensional bundle where an employer does indeed exchange money for labor time.

This dichotomy is clearly inadequate to describe the wide heterogeneity of jobs that can be found in the labor market. Some jobs such as law clerk to a Supreme Court Justice, Junior Fellow at Harvard, post-doc in the Chemistry Department at Chicago, or copilot on a DC–9 can properly be classified as *stepping stones*.[1] Additionally, some positions are viewed as "permanent" by both employer and employee even though the normal job tenure falls short of the working career of a typical individual. This is likely to be the case when performance depends on physical fitness. Policemen, chicken sexers, firemen, ballet dancers, and advertising jingle singers will leave their primary jobs well before the normal retirement ages of 62 and 65. Physical fitness is not the only reason for short working careers. Stress, poor promotion opportunities, or changing preferences may account for the relatively brief job tenures for nurses, mobility instructors for the blind, and floor traders.

The dual labor market can be expanded to a taxonomy identifying at least four types of employment relations, namely permanent primary-sector jobs, casual secondary-sector jobs,

stepping stones that emphasize training, and limited-tenure positions. Military service surely belongs to the fourth category. Stafford raises the question, "What is an optimum duration for an Army career?"

II. Pay, Training, and Post-Service Earnings

The parties to an employment relation enter into an implicit agreement about what constitutes performance and an explicit arrangement about the compensation for performance. The wide variety of jobs is characterized by complex bundles of tasks, responsibilities, and working conditions, as well as compensation packages that contain different components. Stafford writes: "The idea is, when signing up, enlistees in the Army are committing to a time path of several variables, pay training, and output in the Army. . . . Second, the payoff in the civilian labor market will differ across military occupations making skill acquisition and post-Army benefits a larger share of the attraction of enlisting." The compensation needed to attract and retain qualified personnel will depend on the make-up of the composite bundle. Some components such as the number of permanent change-of-station moves imposed upon a service member are endogenous decision variables, while others such as the wage rate in the local labor market (which affects the utility of spouses and moonlighters) are exogenous externalities. The post-service earnings trajectory is a component of the job bundle that can affect the value of an Army career, thereby influencing the reservation wage along the enlistment supply curve.

III. The Theoretical Model

In setting up the model, Stafford assumes that an Army career is characterized as "fulfilling a contract made under perfect foresight." Given this assumption, the duration of an Army career is evidently optimally chosen at $t_1 - t_0$ periods. During this stint in the Army, the soldier can consume, invest in human capital, or vary his or her stock of financial assets R.

(1) $U_a = A(M_1)$ (Army utility function)

(2) $\dot{K} = a(sK) - dK.$ (net investment in human capital)

(3) $\dot{R} = (1 - s)W_aK - M_1P_1$ (asset accrual)

where W_a (which is my substitution for Stafford's alpha) stands for the Army rental rate on human capital. There are three corresponding equations for the post-service career that extends from separation at t_1 to the finish of the working life at t_f; these are:

(4) $U_c = C(M_2),\ \dot{K} = c(sK) - dK,\ \dot{R} = (1 - s)W_cK - M_2P_2$

where W_c is the civilian rental rate, and s is the fraction of a period allocated to training as opposed to production.

The implicit time cost of training is completely borne by the trainee. The transition from the Army to the civilian "after" market is assumed to entail a lump sum mobility cost of C. A higher rate of Army pay, meaning a larger value for W_a, raises the return to Army human capital resulting in a decrease in s, the fraction of time allocated to invest in K. Stafford claims that an increase in W_c gives the soldier an incentive to "shirk." In the context of the model, this means allocating more time to training and less $(1-s)$ to producing Army output. The decision variables in this model are the fraction of time allocated to training, s, and the proportion of income allocated to consumption. Given perfect foresight, the duration of the Army career is optimally chosen at t_1.

Stafford does not analyze the way in which rental rates, (W_a, W_c), or the efficiency of investing in human capital, the properties of a(sK) and c(sK), might alter the fraction of the fixed working life $(t_f - t_0)$ that is allocated to the Army career. A more serious drawback is that the model identifies only one type of human capital, K. The rental rates are, however, different in the two markets. Later, Stafford suggests that W_a and W_c might depend on the individual's military occupational specialty, MOS, but this dependence is not incorporated into the dynamic model. "Skill building measured by rapid promotions or by years of military experience may get more highly rewarded in the civilian labor market." The specificity of military training and the relation of Army pay to alternative civilian earnings surely affect the incentives to acquire military training as well as the decision to reenlist. These suggestions are never incorporated into the formal model.

IV. Grouped Data and Linear Aggregation

The Post-Service Earnings History File cannot be linked to the individual's file from the Defense Manpower Data Center. Stafford is thus forced to use grouped data where "cells" can be defined by the following characteristics: (1) branch = Army; (2) years of military experience that I shall label as Mil-X; (3) education; (4) pay grade level; (5) year of expiration of term of service (ETS), which can be converted to post-service civilian labor market experience, Civ-X; and (6) military occupational specialty, MOS. Within each cell, he computed various "carry-along" variables such as the percentage of individuals who are female, black, with different levels of educational attainment, different numbers of dependents, marital status, home state, etc.

There are at least two problems when regressions are based on grouped data. If the log of earnings is related to years of experience X and its square, X^2, the square of the mean is *not* equal to the mean of the squares. Consider a cell that contains 10 individuals: 5 with X = 2 years of experience, 2 with X = 5, 2 with X = 7, and 1 with X = 12 years. The mean years of experience in this cell is $\bar{X} = 4.6$ and $\bar{X}^2 = 21.16$. However, $\Sigma X_i^2/N = 31.2$, and it is the latter mean that should be on the right side of the earnings equation. The larger is the within-cell dispersion, the bigger is the gap between the square of the mean and the mean of the squares. A similar arithmetic discrepancy will occur for interacted variables.

A second and more serious problem arises if different parameter vectors apply for individuals within a cell. If females have flatter post-service earnings profiles, the use of cell means will produce the kind of linear aggregation bias analyzed by Henri Theil (1971). It would be helpful if Stafford could give us more guidance in the way in which cells were defined. The sample sizes for the regressions in Table 7.3 are considerably smaller than the sample sizes for the regressions in Table 7.4, which are limited to soldiers with fewer than 20 years of service. Why?

V. Post-Service Earnings Equations: A First Approximation

The preliminary regressions reported in Table 7.1 are based on the Social Security Administration earnings data in original values. Since they cannot be easily compared to the log-earnings equations, I shall refrain from discussing them. The first approximations that are based on the logs of mean Internal Revenue Service (IRS) earnings are reported in Table 7.2. The dependent variable, Y_i = log of mean IRS earnings in 1980, is regressed on seven explanatory variables. I reproduce below the parameter estimates for four of the explanatory variables where an asterisk indicates a t-ratio of 2 or more. Two variables, Civ-X and Education, account for nearly all of the explained variance. Military experience and AFQT are insignificant. The coefficient of the percentage of females is unbelievably big and probably reflects the effects of a linear aggregation bias. I would urge that the regressions be run separately for men and women, if that is possible.

Variable	Combat	Admin	Mechan
1. Civ-X	.063*	.063*	.053*
2. Mil-X	–.002	–.94E-3	–.53E-3
3. AFQT	–.99E-3	.33E-3	.006*
4. Education	–.069*	.056*	.028
R^2	.1819	.2817	.1985
Sample Size	513	681	495

VI. Further Refinements

In Table 7.3, over 30 explanatory variables are included in the post-service earnings equations. The data were evidently available by single years of military experience. Stafford was able to include dummy variables for 5, 6–7, and 8–9 years of military experience where YOS = 3, 4 is the base group. The coefficients of the dummies for 5, 6–7, and 8–9 years of Army service were respectively .138, .092, and –.03 (When the pay grade variable is deleted, these coefficients climb to .181, .164, and .074.) Stafford interprets the declining payoff to Army experience as some form of selective attrition. People with better civilian opportunities leave earlier. Before remarking on these results, let me reproduce a few of the OLS parameter estimates.

Variable	(1)	(2)
1. Civ-X (months)	.0115	.0119
2. Civ-X^2	−.79E-4	−.41E-4
3. Mil-X (months)	−.21E-3	.14E-3
4. Mil-X^2	.23E-5	−.21E-5
5. % in the Mil MOS	.0057	−.0020
6. % in Mon-Mil Mos/Sup	.0215*	.0191
7. Pay Grade	.0019	—
R^2	.4174	.3870
Sample Size	287	287

Military experience seems to have been included twice, once in months and its square, and again as a set of three dummy variables. I am not surprised that Mil-X and Mil-X^2 were insignificant. Notice that Civ-X and its square, Civ-X^2, are not statistically significant when they are measured in months rather than in years. This may be due to the discrepancy between the square of the mean as opposed to the mean of the squares. Finally, the largest coefficient is observed for individuals with five years of military service. It would be interesting to estimate separate post-service earnings equations for samples stratified by years of military service to see if the coefficients of Civ-X and Civ-X^2 differ across samples.

The last refinements are reported in Table 7.4 for individuals with 20 years of Army service and for 1983 IRS earnings. I again reproduce a few of the OLS parameter estimates.

Variable	Combat	Admin	Mechan
1. Civ-X	.058*	.084*	.092*
2. Civ-X^2	−.74E-3	−.0022	−.0018
3. Mil-X	.035*	.068*	.066*
4. Mil-X^2	−.0015*	−.0028*	−.0025*
5. Civ-X x Mil-X	−.31E-3	−.63E-3	.0027*
6. AFQT	−.76E-3	−.0019*	.0025*
7. Education	.043*	.077*	.051*
8. Pay Grade Gap	.139*	.148*	.131*
R^2	.3569	.5227	.4734
Sample Size	1,493	1,915	1,430

Mil-X is now statistically significant, but the service tenure that maximizes the log of post-service earnings is well beyond the five years found in Table 7.3. Given the earlier result, I am

surprised that Stafford did not embrace a nonparametric approach on the effect of Mil-X on the logarithm of post-service earnings.

I am not sure if I fully understand the pay-grade gap variable. As I read this description, Stafford constructs an expected pay grade, EPG, by MOS, m, and years of service, x; EPG(m,x). Each cell in his sample is identified by (m,x); and for the j-th cell, he calculates the average pay grade, $APG_j(m,x)$. The pay grade gap is given by either,

$$G_j = APG_j(m,x) - EPG(m,x) \text{ or } G' = -G.$$

The coefficients of G are in the neighborhood of +.14 meaning that a one-grade-level increment raises the post-service earnings by around 15 percent. If separate post-service earnings equations are estimated for each MOS group, the inclusion of average pay grade for the cell would have sufficed *if* military experience had been measured by a vector of dummy variables.[2]

VII. Further Thoughts on Army Pay, Training, and Post-Service Earnings

In Stafford's model, Army pay and post-service earnings are proportional to stocks of human capital where the proportionality factors are the rental rates (W_a, W_c). For the purposes at hand, it might be helpful to deal not with rental rates, but rather with annual earnings of Y_{At} in the Army and Y_{Ct} in the post-service civilian sector. Let VA(t) and VC(t) denote the expected present values of earnings in the Army and civilian labor markets. If q_t is the likelihood of remaining in the Army, and B = 1/(1+r) is the discount factor, we have

$$\text{(5)} \qquad VA(t) = q_t Y_{A,t} + q_{t+1} B Y_{A,t+1} + q_{t+2} B^2 Y_{A,t+2+\ldots}$$

$$\text{(6)} \qquad VC(t) = (1 - q_t) Y_{C,t} + (1 - q_{t+1}) B Y_{C,t+1} + \ldots$$

If training is ignored, a soldier remains in the Army so long as VA(t) > VC(t). He separates at time T* where VA(T*) < VC(T*). The Army can exercise some control over T* by altering the time path of Army pay, (Y_{At}), through reenlistment bonuses, accelerated promotions, increases in BAS/BAQ, or even pensions. Training can influence duration T* in at least two ways. First, Army training that is military specific may raise (Y_{At}) as

well as the soldier's productivity X_t in the Army. Second, training as a helicopter pilot could enhance Y_{Ct}. Such favorable and transferable training will encourage early separation, meaning a decrease in T* unless the Army reacts by increasing the present value of staying in the Army, VA(t). The relation between the amount of training given to the soldier (as well as on-the-job training via military experience) and her productivity, X_t, has traditionally constituted the weakest link in designing the pay profile as well as the experience structure of the force.

Notes

1. The terminology is borrowed from Borjas and Rosen (1980) who argued that the wage change accompanying a job switch will depend on whether the prior job was a stepping stone or a "permanent" job.

2. The expected pay grade is obtained by regressing average pay grade on a vector of dummy variables describing years of service, YOS, which is nothing more than Mil-X. Since EPG is a linear function of this vector of YOS, then inclusion of the average pay grade, APG_j, would have been equivalent to this more complicated pay grade gap variable. However, if we included a vector of YOS dummy variables, Mil-X and Mil-X^2 should not be put into the regression equation.

8

The Army College Fund: Effects on Attrition, Reenlistment, and Cost

Paul F. Hogan
D. Alton Smith
Stephen D. Sylwester

I. Introduction

Since the end of conscription in 1973, educational benefits for military personnel have been analyzed primarily for their potential effects on the supply of recruits to the Armed Forces. In this paper, we analyze the effects of the Army College Fund (ACF)— a special Army-specific educational benefit— on attrition, reenlistment and costs, using data from a 10 percent sample of the Army FY 1982 recruit cohort. The ACF offered the opportunity for qualified recruits entering selected skills to receive supplementary educational benefits over and above the basic educational benefits available to all recruits in all services. The analysis is limited to the program that was in effect from FY 1982 through FY 1985. Though the benefit levels were modified in FY 1986, these results provide insight into the likely effects of the current ACF program and provide some of the evidence necessary for a more complete evaluation of educational benefits as a tool to improve force manning.

Our results suggest that the supplementary educational benefits ("kickers") offered under the ACF have a positive, but small and statistically insignificant effect on the probability that a recruit will remain in service over his initial term. These

benefits do, however, reduce the probability that the recruit will choose to reenlist. We estimate that soldiers who enlist for three or four years and are eligible for kickers have a 5- to 6-percentage-point lower reenlistment rate than those who are not eligible. Those eligible for kickers who enlist for two years have about a 10-percentage-point lower reenlistment rate than other two-year recruits. Finally, the benefit usage model permits us to predict the present value of educational benefit costs of a recruit as a function of his characteristics and the benefits offered. Based upon our model of usage, the present value of the educational benefit costs generated by a high school graduate scoring in the 80th percentile on the Armed Forces Qualification Test (AFQT), who is eligible for supplementary benefits and who leaves at the end of the first term of service, is about $2,300.[1] Not surprisingly, those eligible for kickers have a much higher probability of using any benefits and use significantly more of their benefits, on average, than otherwise similar soldiers who are not eligible for kickers.

II. Background

For recruits entering the Armed Forces after December 31, 1976, the Veterans Educational Assistance Program (VEAP) replaced the more generous Vietnam-era GI Bill. The primary purpose of the Vietnam-era GI Bill was to serve as partial compensation and readjustment assistance during the period of conscription. Nevertheless, its persistence into the All-Volunteer Force (AVF) era served as a powerful recruiting incentive, offering recruits approximately $300 per month for up to 45 months to attend school.[2] Its replacement, VEAP, offered recruits the opportunity to contribute $100 per month, up to a maximum of $2,700, to a fund that would be matched, two-for-one, by the government. The decline in the supply of higher quality recruits to the Armed Forces, especially in the Army, that occurred in the late 1970's can be explained, at least in part, by the loss of the lucrative educational benefit that was only partially compensated by VEAP.[3]

In response to poor recruiting, Congress sponsored a test of more lucrative educational benefits in 1981. The results of the test, designed and evaluated by the RAND Corporation, suggested that increased educational benefits targeted to the

Army could increase the supply of higher quality recruits to that service without significantly affecting the supply to the other services.[4] The outcome of this test was the implementation of the ACF in FY 1982, which offered qualified Army recruits in selected skills benefits of up to $12,000 in addition to the basic VEAP benefit. Table 8.1 displays VEAP benefit and kicker amounts.

Table 8.1
Army Educational Benefits: VEAP and ACF

Obligation	Contributions			Total Benefit
	Member (VEAP)	Government (VEAP)	Government (ACF)*	
2-Year	$2,400	$4,800	$ 8,000	$15,200
3-Year	2,700	5,400	12,000	20,100
4-Year	2,700	5,400	12,000	20,100

*Offered to high school graduate recruits who scored in the upper half of the AFQT and who enlisted in selected (shortage) skills.

Several studies have attempted to assess the effect that educational benefits have on the supply of recruits (see, for example, Daula and Smith, 1985). However, to develop an efficient combination of recruiting resources and incentives, it is not sufficient to examine the effects on supply alone. Costs and other effects on the supply of qualified people to the Army and the other services must also be considered.

Educational incentives have been hypothesized to affect the behavior of recipient soldiers in at least two ways in addition to the effect on the supply of recruits. First, educational incentives may increase the incentive of a recipient to complete his enlistment contract. That is, educational incentives may reduce the probability of attrition prior to the expiration of the contractually obligated term of service. Second, recipients of large educational benefits may reenlist at lower rates than otherwise comparable soldiers who are not eligible for large educational benefits.

The only previous study to examine the effects of educational benefits on the attrition behavior of soldiers is Schmitz (1988). He found that the educational benefit kickers offered under the ACF did not have a statistically significant effect on

the probability of surviving two years relative to soldiers who were eligible for kickers under the ACF's predecessor, Super VEAP.[5]

Schmitz also examined the effect of educational incentives offered under the ACF on reenlistment behavior. Again, compared to soldiers eligible for kickers under Super VEAP, the ACF kickers did not have a statistically significant effect on reenlistment probability. Thomason (1985), however, in one of the few other studies of this issue, found that U.S. Navy sailors eligible for the Vietnam-era GI Bill had lower reenlistment rates than sailors who were eligible for less lucrative VEAP, after controlling for pay, bonuses, individual characteristics, and other factors affecting reenlistment behavior.

Using a data set similar to the one employed in this study, Schmitz, Dale, and Drisko (1987) estimated the costs of the ACF. Other than the length of the initial term of service, they do not model benefits usage as a function of individual soldier characteristics, such as AFQT and education, and of the amount of benefits to which a soldier is entitled. This limits the usefulness of their analysis in estimating the expected costs of current education-benefits programs.[6]

In this paper, we examine the effect of the ACF on attrition, reenlistment, and cost. The measurement of the effects is based upon differences in the application of kickers across Army skills for the FY 1982 entry cohort. Section III presents simple theories of attrition, reenlistment, and educational benefit usage, and develops testable hypotheses of the effects of educational benefits on behavior. Section IV discusses the data used in this analysis, while Section V discusses the estimation methods. Results are presented and discussed in Section VI. Section VII discusses policy implications, presents an application of these results, and provides concluding remarks.

III. Theory

An Economic Theory of First-Term Attrition

Recruits to the Army enter based upon the benefits they perceive of enlisting in the Army relative to their best civilian alternative. They sign an enlistment contract under which they agree to serve for a fixed period of time, typically two, three, or

four years. They make their decision under conditions of less than perfect information. Actual experience provides them with better information on the net benefits of military service. Based upon the additional information experience provides, some recruits may have regrets and an incentive to default on their enlistment contract by leaving prior to expiration.

On the demand side, the Army may judge that a particular recruit's performance is less than satisfactory and discharge him prior to contract completion. Another way of interpreting this, however, is that the recruit finds it too costly to exert the effort necessary to meet the Army's performance standards and acquiesces to the Army's attrition policy.

"Voluntary" theories of first-term attrition from military service, where "voluntary" connotes elements of choice on the part of the soldier, have been proposed by Hogan (1979), Buddin (1984), and Antel, Hosek, and Peterson (1987). Most models of first-term attrition, however, have been purely statistical, with little or no theoretical underpinning. We present a simplified theory of the first-term attrition decision below.

The individual makes a decision to enlist at time t_0 for a term of enlistment of length l. Let $B^e_{t',i}$ (l) be the expected net benefits the individual perceives at time t′ of enlisting for a contract of length l. These benefits will consist of two components. First, there are the net pecuniary benefits of enlisting in the Army—the difference between earnings while in the Army and potential civilian earnings over the period of enlistment, and perhaps the effect that Army experience will have on future civilian earnings. The second component is the value the individual places on the nonpecuniary differences between Army and civilian life. However, the perceived benefits of enlisting will differ from the actual benefits by an error term reflecting imperfect information.[7] Let $e_{t',i}$ be the error. It is assumed to be distributed randomly and with mean zero among *potential* recruits.[8] We may write:

(1) $$B^e_{t',i}(l) = B^a_{t',i}(l) + e_{t',i}$$

where $B^a_{t',i}$ is the actual net benefits of enlisting. Intuitively, those members who will have an incentive to break their contract, once they enter, are those for whom

(2) $$B^{e}_{t',i}(l) > 0 \text{ but } B^{e}_{t',i} - e_{t',i} < 0$$

Upon entering the Army, the recruit "learns" over time so that $B^{e}_{t'+s,i}(l) = B^{a}_{t'+s,i}(l)$ at time $t'+s$; that is, the individual's perception converges to the true benefits. At $t'+s$, define the net benefits of completing the contract as

(3) $$B^{a}_{t'+s,i}(l) = \sum_{t=t'+s}^{t'+l} (M_{i,t} - C_{i,t} + P_{i,t})(1+r)^{-(t-(t'+s))}$$

where

- $M_{i,t}$ is the expected pecuniary benefits of remaining in the Army at time t;
- $C_{i,t}$ is the pecuniary benefits that would accrue to a soldier if he were in the civilian sector at time t;
- $P_{i,t}$ is the individual's evaluation of the net non-pecuniary differences between being in the Army and being in the civilian sector at t; and
- The soldier's discount rate is r, and l is the length of his enlistment contract.

The soldier will break his enlistment contract if

(4) $$B^{a}_{t'+s,i}(l) < D_{t'+s,i}$$

where $D_{t'+s,i}$ is the cost to the individual of breaking a contract by leaving at time $t'+s$.[9] We assume that, for an individual, $D_{t,i}$ is constant for all l, and that $D_{t'+l,i}$ is zero.[10]

Reduced Form Empirical Specification

In the empirical specification, factors associated with the benefits and opportunity costs of completing an enlistment contract are included, along with factors affecting the individual's cost of default. A number of demographic variables are included. We suggest a structural interpretation to these variables, based upon the benefits and costs of attrition. In most previous empirical work, however, demographic variables have been interpreted largely as reflecting natural "propensities" rather than as being associated with individual choice. In a reduced-form specification, some factors will be associated with both the benefits

and the costs of completing an enlistment contract. For example, factors associated with innate ability, such as the AFQT score, may affect the costs incurred by the member to meet minimum performance standards but may also affect the member's civilian opportunities. The estimated coefficient will be the sum of these potentially conflicting effects.

Educational benefit kickers are hypothesized to increase the probability that an individual will complete his enlistment contract for at least two reasons. First, though there are exceptions, a member must have contributed to basic VEAP for at least one year in order to qualify for the kickers. Second, total educational benefits "earned" increase with VEAP contributions. Hence, the member who enlists for a kicker has an incentive to remain in the Army sufficiently long to "earn" the benefits.

The following variables are included in the reduced form specification of the attrition model:

Enlistment Contract Duration. Inspection of equation (4) suggests that the individual compares the fixed costs of breaking an enlistment contract with the costs of waiting until contract expiration (ETS). The closer to ETS, the less likely it is that the member will find it desirable to break the contact because the period over which net costs will be incurred $(1 - s)$ is small. The costs of waiting are likely to be small relative to the costs of breaking the contract. Hence, one would expect that the shorter the contract duration the lower the attrition.[11]

Education. Education may lower the cost to the member of meeting performance standards. It is also associated with better civilian opportunities, and may raise the costs to the individual of defaulting on an enlistment contract.[12]

Gender. Women may face a different cost of breaking an enlistment contract than men, other things being equal. Army discharge policies are different for women, and the civilian labor market may not value completion of an Army enlistment in the same way for males and females.

Race. We speculate that blacks may break their enlistment contracts at lower rates than nonblacks for two related reasons. First, earnings opportunities in the Army relative

to the private sector are greater for blacks than for nonblacks. Second, the value that the civilian labor market places on enlistment contract completion may be greater for blacks compared to nonblacks.

AFQT Score. Soldiers with higher AFQT scores may find it easier to meet performance standards. However, these soldiers may also have better civilian opportunities.

Occupational Category. Nonpecuniary aspects of Army service vary by MOS. Moreover, the value of Army training in the civilian sector will vary by MOS, suggesting that attrition rates will vary by skill.

Months in the Delayed Entry Program (DEP). Previous research has shown that those who have spent more time in the DEP tend to have lower attrition rates after entry, other things being equal. There is not likely to be a causal relationship. Rather, time in DEP probably serves as a screening device, and is correlated with unobservable factors affecting attrition.[13]

Educational Benefit Kickers. Kickers increase the value of contract completion and therefore should reduce first-term attrition.[14]

Reenlistment Behavior

Theories of reenlistment behavior are more highly developed and have been the subject of greater empirical testing than have theories of first-term attrition. Economic theories of reenlistment behavior typically view the reenlistment decision as one of occupational choice. They are based on rational behavior, assuming that the individual chooses the option offering the greatest benefits, both pecuniary and nonpecuniary. The extensive literature on reenlistment behavior is reviewed by Black, Hogan, and Sylwester (1987).

Our interest in the reenlistment behavior of Army first-term soldiers is the effect that eligibility for educational benefit kickers has on the decision to reenlist. Educational benefit kickers lower the expected cost of obtaining additional education, making that option relatively more attractive. Since additional education can be most efficiently obtained while not on active duty, and because additional education is likely to

raise future civilian earnings relative to future military earnings, kickers increase the incentive to leave at the reenlistment point.[15]

The effect of kicker eligibility on reenlistment behavior is complicated by self-selection in the kicker population. Many who choose to enter skills offering kickers indicate that they do not intend to make the Army a career. Their (*ex ante*) taste for Army life may be systematically correlated with their decision to enter a skill offering kickers. Hence, there are conceptually two ways in which kickers are associated with reenlistment probability. First, kickers directly affect the benefits of reenlisting relative to the benefits of leaving. Second, the individual's choice of a kicker skill is correlated with other factors affecting reenlistment probability. We do not attempt to sort out these two effects.[16]

Reduced Form Empirical Specification

In this reduced form specification factors affecting military and civilian earnings, as well as nonpecuniary aspects of Army service, are included. Structural measures of expected military and civilian pay, which have a large effect on the expected net benefits of reenlisting, are not included. Care must be taken in interpreting the effects of the demographic and other variables as solely "taste" or sociological variables, because some or all of their influence may be through their relation to pecuniary benefits.

The following variables are included in the reduced form specification of the reenlistment equation:

Education. Civilian earnings opportunities will vary with the level of education.

AFQT. The Armed Forces Qualification Test score attempts to measure the innate ability or aptitude of the individual. To the extent that it does so, both military and civilian earnings will vary with this measure.

Black. Differences in reenlistment behavior by race may measure systematic differences in civilian earnings opportunities, or differences in "tastes" for military service.

Female. Differences in reenlistment behavior by gender may measure systematic differences in civilian earnings opportunities by gender, or differences in taste.

Enlistment Contract Length. Enlistment contract length captures two effects. First, those who choose longer initial obligations are probably more confident that they want to make the Army a career. Hence, contract length is correlated with taste for military service. Second, since all recruits in the data set entered in the same year, enlistment contract length is similar to including year-of-reenlistment dummies, capturing differences in the incentive to reenlist for those making the reenlistment decision at different points in time.

Reenlistment Bonus. Bonuses increase the pecuniary advantages of reenlisting, and therefore the incentive to reenlist.[17]

Military Occupation. Nonpecuniary factors of military service will vary by skill or occupational category. The value of military training and experience in the civilian sector will vary among military skills, affecting civilian earnings opportunities.

Kickers. Kickers reduce the relative attractiveness of reenlisting, increasing the expected benefits from additional schooling.

Usage of Educational Benefits

Usage of educational benefits is assumed to be directly related to the amount of post-service education demanded. A simple equation describes the key elements of this demand.

The net financial benefits of N additional years of education are:

$$B = \int_{t'}^{t'+N} [-(W_t(0) + C_t) + K_t]e^{-r(t-t')}dt + \int_{t'+N}^{T} [W_t(N) - W_t(0)]e^{-r(t-t')}dt \tag{5}$$

where

- $W_t(N)$ is the individual's wage at t, after N additional years of education;
- C_t is the cost of education at time t, exclusive of the value of the individual's time; and
- K_t is the subsidy to education at t, presumably due to educational benefits earned in military service.

The first part of (5) is the cost of attending school for N years. This includes forgone earnings at the wage $W_t(0)$ and tuition and expenses, C_t, net of the ACF subsidy, K_t. The second part of the expression is the present value of the increased earnings due to N additional years of schooling, $W_t(N) - W_t(0)$.

The individual chooses N to maximize B. Maximizing equation (5) with respect N and scaling t so that t′= 0, we obtain the marginal condition that:

$$[-(W_N(0) + C_N) + K_N - (W_N(N) - W_N(0)]e^{-rN} + \int_N^T dW_t(N) / dN \, e^{-rt} \, dt = 0 \tag{6}$$

$$\text{or} \quad (C_N - K_N) + W_N(N) = \int_N^T dW_t(N) / dN \, e^{-rt} \, dt$$

In words, at an interior solution, additional years of education will be pursued until the increase in the present value of future earnings from the additional education (the right-hand side) is equal to the costs of the additional education (net of the kicker subsidy) plus the forgone earnings resulting from the additional time spent in school rather than in the labor market.

Since the (discounted) costs to the Army of the ACF for individual i are simply:

$$\int_0^N K_t \, e^{-rt} \, dt \tag{7}$$

those factors that tend to increase N will increase the costs of the ACF. From equation (6) we note, first of all, that the larger

the ACF subsidy, K_t, the greater will be the optimal number of years of education, N. Hence, we reach the commonsense conclusion that those members eligible for large kickers are likely to incur larger costs than those who are not eligible. Second, individuals for whom the increase in earnings from additional years of education are the greatest are, other things being equal, likely to invest in more years of schooling and incur higher ACF costs. For example, if innate ability or aptitude is complementary with education, we expect usage rates to be greater for individuals with higher AFQT scores, other things being equal. Finally, those individuals for whom $W_t(0)$ is already large, either in the Army or in the civilian sector, are less likely to demand additional years of schooling. For example, members who already have a college degree will be less likely to demand additional years of schooling, other things being equal.

Reduced Form Specification

The following variables are included in the reduced form specification for benefits usage:

Armed Forces Qualification Test Score. If education is complementary with innate ability or aptitude, individuals with higher AFQT scores should use more of their benefits. In the terms of the theoretical model, the effect on earnings of an additional year of education is likely to be greater for those with higher aptitudes.[18]

Education. The level of education will affect usage in three ways. First, higher levels of education increase the individual's potential civilian earnings, and therefore the opportunity cost of additional years of education. Second, the effect of education may be directly related to a degree. A "sheepskin" effect would suggest that the marginal year of education that results in the completion of a degree may be particularly valuable. These two effects together suggest that college graduates will demand less additional education than those with "some college." Third, a high school diploma is often a prerequisite for college. Hence, those who are not high school graduates may not be eligible for higher education.

Demographic Characteristics. Race, gender, and marital status may capture both factors affecting the opportunity cost of additional education and tastes.

Kicker. If the individual is eligible for an ACF kicker, the price of education is lower and the individual is likely to consume more.[19]

Months Since Leaving Service. Because our data on usage of educational benefits ends in September 1987, not all individuals will have had the same opportunity to use their benefits.

IV. Data

The data consists of a 10 percent sample of nonprior service personnel recruited and accessed into the Army active enlisted force during FY 1982. There are 8,089 usable observations at the entry point. Individuals were followed from the time they enlisted until September 1987. If they used ACF educational incentives, the month and amount of use is recorded by combining files from the U.S. Army Finance and Accounting Center (USAFAC) and the Veterans' Administration.

In all cases, we infer eligibility for ACF kickers based upon the recruit's Military Occupational Specialty (MOS), education, and AFQT score. This information is available at the time of accession. We do not use information on actual participation in the VEAP program, for example, to determine eligibility. VEAP participation is, itself, an endogenous variable—something to be explained. To use it, or information similar to it, may tend to bias the parameter estimates, making the model less useful for policy purposes.

Attrition models are estimated for the probability of surviving 13 months, 22 months and to within three months of ETS. Reenlistment models were estimated for that portion of the population that stayed in the Army until at least within three months of ETS. A "reenlistment" was defined as remaining in the Army at least three months beyond ETS.[20] The sample for estimating ACF usage consists of those who stayed at least to within three months of ETS, and then left.[21] Table 8.2 summarizes the sample sizes and the mean of the dependent variable for each model.

Table 8.2
Sample Size

Model	Sample Size	Mean of Dependent Variable
Attrition		
Stay 13 months	8,089	.89
Stay 22 months	8,089	.82
Stay until ETS	8,089	.73
Reenlistment		
All	5,926	.46
3/4 year contracts	5,402	.48
Usage	2,802	see below

Because the data end in September 1987, the number of months available for using benefits provided by the ACF will vary systematically by the length of the initial enlistment contract. We have a maximum of 48 months of observations on individuals who entered with two-year contracts and left at ETS. Similarly, for those who entered under three-year contracts we have a maximum of 36 months after leaving at ETS, while there will be a maximum of 24 months of observations for those who entered with four-year contracts.[22]

Table 8.3 presents means of the explanatory variables for the samples used in each of the models, while Table 8.4 presents descriptive statistics for the usage data.

Table 8.3
Descriptive Statistics: Variable Means

	Attrition	Reenlistment	Usage
AFQT	51.1	51.2	49.9
GED	2.0%	1.5%	1.6%
HS Graduate	82.0%	83.8%	85.0%
Some College	6.7%	7.4%	6.3%
College Graduate	2.1%	2.1%	1.4%
2-year Enlistment	6.7%	8.0%	
4-year Enlistment	37.8%	36.0%	
Months in DEP	1.6		
Kicker	30.0%	31.7%	57.8%

Table 8.3 (continued)
Descriptive Statistics: Variable Means

	Attrition	Reenlistment	Usage
Black	25.3%	26.8%	2.8%
Other Ethnic	4.9%	5.0%	4.7%
Female	10.9%	10.0%	8.2%
Married	12.7%	12.2%	5.0%
SRB Multiple		0.49	
T (months since leaving)			24.0

Table 8.4
Descriptive Statistics: Benefits Usage

	Rate[a]	Average Amount[b]
Usage: Entry Cohort		
All	.12	$ 637
Kicker	.26	1,939
$8K	.43	4,750
$12K/3YO	.22	1,555
$12K/4YO	.19	1,039
No Kicker	.05	170
Usage: Those Who Left at ETS		
	Rate	**Average Amount**
All	.27	$1,685
Kicker	.52	3,924
$8K	.67	6,525
$12K/3YO	.47	3,347
$12K/4YO	.45	2,342
No Kicker	.14	445

[a]Proportion using some educational benefits.
[b]Including those using no benefits.

V. Estimation Method

Three types of models are estimated: a model of attrition behavior, a model of reenlistment behavior, and a model of educational benefit usage. We have argued that the latter is, in fact, a model of the demand for education.

Probit Models of Attrition and Reenlistment Behavior

Both the attrition and reenlistment models are estimated as probits. For example, the individual member will stay at least one year if

(8) $$XB + e > 0$$

where X is a vector of explanatory variables related to the benefits and costs of completing at least one year of service, and e is an unobserved random component of these costs and benefits.

The unobserved random component is assumed to be distributed normally across individuals, and have zero mean and variance equal to 1. The probability that a given individual will stay at least one year is equal to

(9) $$\text{Prob}\,(XB + e > 0) = \int_{-XB}^{\infty} f(e)\,de$$

where f(e) is the density function of e. This is a probit model. The reenlistment model is defined analogously.

A Tobit Model of ACF Usage

In the model of educational benefit usage developed in Section III, the usage of the ACF was related directly to the demand for additional years of education. Let X_i be a vector of the factors affecting education for individual i, and B be an associated vector of coefficients. Then

(10) $$Y_i = X_iB + u_i$$

where Y_i is the dollar denominated usage of individual i. The term u is an unobservable component affecting usage and is assumed to be distributed standard normal over the population. However, we do not observe negative usage. For those for whom usage is zero, we know only that

(11) $\text{Prob}\,(Y_i = 0) =$

$$\text{Prob}\,(u_i < -XB_i) = \int_{\infty}^{-XB} f(u)\,du = (1 - F(X_iB))$$

where F is the cumulative normal distribution function.

For observations for which there is positive usage of educational benefits, we have:

$$\text{Prob}(Y_i>0)\ f(Y_i \mid Y_i>0) = f(Y_i) \tag{12}$$

This setup is estimated using a censored regression or "tobit" model. The likelihood function is

$$L = \sum^{n1} (1-F(X_iB)) + \sum^{n2} f(Y_i-X_iB) \tag{13}$$

with n1 observations of zero usage and n2 observations with benefits usage greater than zero.

Note that the expected value of Y_i is equal to the probability that the individual uses a positive amount of his or her educational benefits multiplied by the expected amount he or she uses, conditional upon using a positive amount:

$$E(Y_i) = F(X_iB)\ E[X_iB + u_i \mid u_i> -X_iB] \tag{14}$$

Understanding the nature of the tobit model is important in interpreting the results. Each explanatory variable has, in a sense, two effects: an effect on the probability of using any of the benefits and an effect on the amount of the benefit used, given that a positive amount is consumed.

Sample Selection Bias and Usage Behavior

An obvious practical application of the ACF usage model is to predict the cost of the ACF, or similar programs, under different conditions, such as different benefit levels, or different eligibility requirements, for an entry cohort of recruits. However, the model is estimated using a sample of recruits who left the Army at the first term of service. It is necessarily a "self-selected" sample.

The tobit model addresses one sort of sample selection bias. We estimate the model for all those who leave at the first term of service, not simply for those who used the benefits. The tobit model predicts changes in the usage rate and amount used for this group, and not simply changes in the amount used among those who used a positive amount.

There are a number of other sample selection issues that are not directly addressed by the model, however. For example, the model is estimated for a given reenlistment rate. If the proportion reenlisting at the first term were significantly lower (or higher) than was the case in our sample, it is not clear that the model's parameters would accurately describe the savings (or additional cost) from the marginal group.

For example, consider a lower reenlistment rate resulting from a reduction in funds allocated to reenlistment bonuses. It is plausible that the usage rate of the group induced to leave because of the lower bonuses would be lower, on average, than the group who would have left in either case. Moreover, this reduced propensity to use educational benefits may be due, in part, to unobservable differences between the two groups — differences not captured by the explanatory variables in X. Stated another way, those who leave when bonuses are relatively high may have a higher average taste for additional education than those who leave only when bonuses are relatively low. Hence, they will use the benefits more intensively than the ostensibly similar group.

We can express this dependence formally by simultaneously considering both the reenlistment equation and the usage equation. Consider a probit model of reenlistment behavior and, to simplify the exposition, a linear usage model. The probability of reenlistment is

$$\text{Prob}\,(R_i = 1) = \text{Prob}\,(X_{ri}B_r + u_{1i} > 0) \tag{15}$$

and the usage equation is

$$Y_i = X_iB + u_{2i}. \tag{16}$$

If the average usage rate varies with the reenlistment rate due to unobservable factors, then $\text{Cov}\,(u_1,u_2) \neq 0$. Estimating the usage equation without recognizing that the estimate is conditional on the reenlistment rate may result in biased parameter estimates because

$$E[Y_i \mid R_i = 1] = X_iB + E(u_{2i} \mid u_{1i} < -X_{ri}Br) \tag{17}$$

and $E[u_{2i} \mid u_{1i} < -X_{ri}B_r] \neq 0$, if $\text{Cov}\,(u_1,u_2) \neq 0$. Biased parameter estimates result if the explanatory variables in the

usage equation are correlated with the unmeasured factor(s) affecting both usage and reenlistment.

To test this possibility, we estimated the reenlistment equation jointly with the tobit usage equation, allowing for a nonzero covariance in the errors.[23] Based on the results, we could not reject the hypothesis of zero covariance. The results reported below are for independently estimated reenlistment and usage equations.[24]

VI. Results

The hypotheses concerning the effects of educational benefits on attrition, reenlistment, and usage derived in Section III, were tested using the data described in Section IV and the methods of the previous section. The results are presented in this section.

The effects of ACF kickers are estimated relative to the basic VEAP benefits. The opportunity to participate in VEAP is offered to all recruits, so that there is insufficient variability to estimate its effects. In interpreting the results, it is important to consider that VEAP may, itself, have an effect on attrition and reenlistment behavior relative to the case of no educational incentives, but we do not estimate this effect.

Attrition

Our hypothesis is that educational benefits increase the advantages to the member of completing a term of service, and therefore reduce the probability of attrition. In Tables 8.5, 8.6, and 8.7, the effects of educational benefits and other variables on the probability of completing one and two years of service, and of surviving to the completion of the initial term of obligated service, respectively, are presented.[25]

The results displayed in Table 8.5 suggest that an educational benefit kicker under the Army College Fund did not have a significant effect on the probability of surviving one year of service. Though the coefficient is positive, it is both practically and statistically insignificant. The results of the probit equation reinforce the well-known result that education is the single most important factor affecting early attrition.[26] Scores on the AFQT are positively related to the probability of survival in this equation, but the effect is not significant.

We also find that the number of months spent in the DEP has a positive and significant effect on the probability of surviving at least a year. However, this may mean simply that high-risk individuals are attriting from the DEP, and are censored in our sample, while the DEP waiting process selects out the more motivated recruits. Our results suggest that blacks have a significantly lower attrition probability, other things being equal, and that attrition is generally higher in the combat arms, the omitted occupational group (OCC0), than in the other occupational categories.[27]

Table 8.6 suggests that the effects of educational benefit kickers on the probability of surviving at least two years is somewhat greater, though the parameter is not estimated at the level of precision that is typically considered "significant." Those with two-year enlistment contracts have a greater prob-

Table 8.5
Stay at Least 13 Months

Variable	Parameter	Derivative	T-Ratio
Constant	0.580	—	5.94
AFQT	0.002	0.000	1.74
GED	−0.090	−0.024	0.72
HS Graduate	0.377	0.076	5.08
Some College	0.406	0.084	3.87
College Graduate	0.337	0.072	2.20
2-Year Term	0.030	0.005	0.34
4-Year Term	0.017	0.003	0.35
Months in DEP	0.052	0.009	5.30
Kicker	0.036	0.006	0.57
Black	0.210	0.034	4.18
Other Ethnic	0.143	0.023	1.55
Female	−0.262	−0.052	4.10
Married	0.020	0.003	0.35
OCC1	0.241	—	2.35
OCC2	0.202	—	3.18
OCC3	0.445	—	3.85
OCC4	0.416	—	2.58
OCC5	0.101	—	1.53
OCC6	0.370	—	5.59
OCC7	−0.047	—	0.26
OCC8	−0.100	—	1.61

Table 8.6
Stay at Least 22 Months

Variable	Parameter	Derivative	T-Ratio
Constant	0.135	—	1.59
AFQT	0.001	0.000	1.30
GED	–0.092	–0.034	0.82
HS Graduate	0.499	0.152	7.68
Some College	0.654	0.188	6.98
College Graduate	0.511	0.155	3.81
2-Year Term	0.130	0.032	1.64
4-Year Term	0.002	0.001	0.06
Months in DEP	0.052	0.013	6.25
Kicker	0.078	0.020	1.42
Black	0.248	0.060	5.67
Other Ethnic	0.123	0.030	1.56
Female	–0.347	–0.100	6.20
Married	0.035	0.009	0.69
OCC1	0.362	—	4.00
OCC2	0.266	—	4.77
OCC3	0.337	—	3.69
OCC4	0.229	—	1.85
OCC5	0.176	—	2.98
OCC6	0.271	—	4.98
OCC7	–0.141	—	0.88
OCC8	–0.026	—	–0.47

ability of surviving two years than do those with three- (omitted group) and four-year contracts, though the parameter estimate is imprecise.

Table 8.7, showing the effect of educational incentives on the probability of competing an initial enlistment term, is consistent with the previous tables. The effect of kickers is positive, adding about 3.5 points to the probability of completing an initial enlistment, but remains statistically insignificant at the levels of significance typically demanded. The results are also consistent with the commonsense proposition that the shorter the initial term of service, the greater the probability of completing it.

Table 8.7
Stay to ETS

Variable	Parameter	Derivative	T-Ratio
Constant	−0.208	—	2.60
AFQT	0.002	0.001	1.76
GED	−0.095	−0.038	0.87
HS Graduate	0.582	0.214	9.40
Some College	0.735	0.261	8.52
College Graduate	0.532	0.198	4.38
2-Year Term	0.356	0.106	4.56
4-Year Term	−0.239	−0.080	6.56
Months in DEP	0.047	0.015	6.31
Kicker	0.078	0.035	1.56
Black	0.199	0.064	5.07
Other Ethnic	0.140	0.045	1.92
Female	−0.418	−0.150	8.11
Married	−0.008	−0.003	0.17
OCC1	0.440	—	5.41
OCC2	0.327	—	6.50
OCC3	0.410	—	4.98
OCC4	0.270	—	2.38
OCC5	0.254	—	4.67
OCC6	0.309	—	6.26
OCC7	0.160	—	1.14
OCC8	−0.017	—	−0.34

In general, then, we find that educational benefit kickers have a positive, but small and statistically insignificant, effect on the probability of remaining in service over the initial enlistment.

Reenlistment

ACF kickers are hypothesized to have a negative effect on the probability of reenlistment. Kickers lower the cost of investing in additional formal education and these investments can be made more efficiently after separating from the Armed Forces. Moreover, those attracted to the Army because of the educational benefit kickers probably have a relatively low

"taste" for military life, compared to those who entered the Army as a possible career choice.[28]

In Table 8.8, the results of estimating a linear model of reenlistment behavior are shown. The effects of kickers on reenlistments for soldiers with initial terms of two, three, and four years are negative and statistically significant. A two-year enlistee eligible for an $8,000 kicker (TOE2-8K) has about a .1 lower probability of reenlisting than an otherwise similar two-year enlistee.[29] A soldier who enlists for three years and is eligible for a $12,000 kicker has a .063 lower probability of reenlisting than an otherwise similar three-year enlistee, while a four-year enlistee has a .057 lower reenlistment probability if he is eligible for a $12,000 kicker. Our results suggest that a two-year recruit who is offered a kicker has about a 0.23 lower probability of reenlisting than a three-year enlistee who is not offered a kicker.

Note that the term of service indicator variables (TOE2YR and TOE4YR) capture at least two effects. First, it is reasonable to assume that the unobservable factors ("tastes") affecting the probability of reenlisting are correlated with the length of initial commitment the member is willing to make. Hence, the term of service variable captures the unobservable factors associated with self-selection at the entry point that also affect the reenlistment probability. Second, the term of enlistment will capture factors affecting reenlistment that vary by fiscal year, such as relative pay and unemployment, because the term of enlistment defines the fiscal year in which the member makes his reenlistment decision.

The results also suggest that blacks, women, and those who are married at entry have significantly higher reenlistment probabilities than others, and that members in most non-combat arms occupations have higher reenlistment probabilities than those in combat arms (OCC0, the reference group).

Table 8.9 presents similar results for those entering under three- and four-year contracts, only, using the probit functional form. A $12,000 kicker reduces the probability of reenlistment by about .06, for those who enter with three-year obligations, and by about .05 for those who enter under four-year contracts,

Table 8.8
Reenlistment Probability (Linear Model)

Variable	Parameter	T-Ratio
Intercept	0.339	8.95
AFQT	0.0004	1.18
GED	–0.029	0.49
HSG	–0.030	0.98
Some College	–0.012	0.30
College Graduate	0.026	0.49
Black	0.155	9.81
Other Ethnic	0.091	3.13
Female	0.109	4.89
Married	0.187	9.66
SRBMUL	0.012	1.50
TOE2YR	–0.129	2.05
TOE4YR	0.077	4.46
TOE2-8K	–0.105	1.58
TOE3-12K	–0.063	2.48
TOE4-12K	–0.057	2.16
OCC1	0.032	1.00
OCC2	0.067	3.33
OCC3	0.109	3.41
OCC4	0.133	2.97
OCC5	0.057	2.54
OCC6	0.019	0.91
OCC7	0.018	0.29

compared to otherwise similar personnel. These represent reductions in the reenlistment rate of between 10 and 15 percent.[30]

It is well to recall that our results are based on one entry cohort. Variation in educational benefit incentives and reenlistment rates is largely the result of cross-sectional variation

Table 8.9
Reenlistment Equation 3/4 Year Enlistment Contracts (Probit)

Variable	Parameter	Derivative	T-Ratio
Constant	–0.42	0.000	—
AFQT	0.001	0.005	1.06
GED	–0.08	–0.032	0.54
HS Graduate	–0.09	–0.036	1.13
Some College	–0.05	–0.020	0.50
College Graduate	–0.11	0.046	0.78
Black	0.40	0.158	9.30
Other Ethnic	0.24	0.098	3.08
Female	0.28	0.114	4.74
Married	0.49	0.195	9.23
4-Year Term	0.19	0.076	4.19
3-Year, 12K Kicker	–0.15	–0.059	2.25
4-Year, 12K Kicker	–0.12	–0.048	1.84
SRB	0.03	0.010	1.14
ADMIN	0.18	0.073	3.42
MECHANIC	0.09	–0.036	1.62
ELECTRICAL	0.18	0.071	3.58
MEDICAL	0.28	–0.113	3.28

among skills. If the selection of skills for the receipt of kickers is systematically related to the level of the reenlistment rate of those skills, and other variables included in the model, such as AFQT and occupational group dummy variables, do not adequately capture this variation, the effect of kickers on reenlistment behavior could be biased.

Usage Results

The usage equations are estimated from data on members who enlisted for three or four years, and who left the Army after completing their initial term of service. We have a censored sample, in the sense that our data on usage ends in September 1987, well before the 10-year limitation on the usage of benefits has expired. Moreover, those in the sample have varying opportunities for using their benefits, depending upon when

and for how long they enlisted. To control for this censoring, we include the variable "T," which is the number of months between the time the member left active service and September 1987, the date of our last observations on usage.[31]

In Table 8.10, the dependent variable is undiscounted dollars in thousands. Because the equation estimated is a tobit equation, each variable has an effect both on the probability of using any benefits and the amount of benefits used, conditional on using any benefits. Hence, we include effects for all separatees, and for that subset who were users.

Eligibility for ACF kickers has the largest effect on usage. Kicker eligibility increases the probability of using benefits by almost 0.60, and increases the usage among separatees by about $4,116. The number of months since separation, T, also has a significant effect on usage. An additional month increases the

Table 8.10
3/4 Year Enlistment Contracts (Tobit)
(Undiscounted Dollars)

Variable	Parameter	Probability of Use	Users	All Separatees	T-Ratio
Constant	−30.70	—	—	—	—
AFQT	0.10	0.047	0.236	0.225	9.61
GED	−2.30	−0.038	−0.324	−0.121	1.02
HS Grad	3.98	0.127	0.732	0.516	3.73
Some College	6.70	0.263	1.407	1.237	5.58
College Graduate	0.42	0.009	0.066	0.033	0.25
Black	−0.29	−0.012	−0.062	−0.054	0.59
Other Ethnic	0.79	0.035	0.174	0.163	0.98
Female	−0.28	−0.012	−0.060	−0.053	0.50
Married	−3.32	−0.114	−0.063	−0.473	4.54
T	1.17	0.043	0.219	0.208	4.29
TSQR	−0.02	−0.008	−0.042	−0.037	3.80
Kicker	12.10	0.596	3.481	4.116	2.48
Kicker*T	−0.56	−0.005	−0.027	−0.024	1.35
Kicker*TSQR	0.09	0.001	0.007	0.007	1.03

probability of using any benefits about .043 and increases usage among all separatees by about $208.[32]

The specification allowed the effect of time since separation on usage to differ for those who are eligible for kickers by interacting T with the indicator variable for kicker. The results suggest that the differences are not statistically significant.[33]

Soldiers with higher AFQT scores are also more likely to use educational benefits. A 10-point increase in AFQT score increases the probability of use by .047, and the amount used by about $225. Perhaps the most interesting result is the high probability of usage and amount of the benefit used associated with those who have entered the Army with "some college." Those with some college have a .263 higher probability of using educational benefits than the reference group, non-high school graduates, and use $1,237 more in benefits. Moreover, the "some college" category uses $721 more in benefits than high school graduates, and $1,204 more than college graduates. Apparently, educational benefits offered under the ACF are especially valuable to those who have started but not completed college, perhaps allowing them to complete a college degree.

Under the Montgomery GI Bill, educational benefit kickers are funded in the accession year of a cohort by depositing the expected present value of future usage costs. In Table 8.11, results are presented when the dependent variable is usage (in dollars) discounted back to the accession point using a nominal discount rate of 8.5 percent. This is the discount rate currently recommended by the DoD's Office of the Actuary. These estimates, then, approximate the usage equations necessary to make actuarial calculations.34 The results are consistent with those in Table 8.10.

VII. Policy Implications

The empirical results presented in this paper are potentially useful to policy analysts and planners in at least three applications. First, they provide information on the full effects of educational incentives, allowing a more complete evaluation of educational benefits as a force manning tool. Second, the estimates of the effects on attrition and reenlistment will allow force planners to consider the effects of educational incentives when projecting the enlisted force inventory, and then to estimate the

Table 8.11
Usage Equation 3/4 Year Enlistment Contracts (Tobit)
(Discounted Dollars)

Variable	Parameter	Effect on Amount Used: Probability of Use	Users	All Separatees	T-Ratio
Constant	–21.60	—	—	—	9.07
AFQT	0.07	0.047	0.165	0.157	9.64
GED	–1.64	–0.038	–0.230	–0.086	1.03
HS Grad	2.77	0.127	0.509	0.359	3.72
Some College	4.65	0.261	0.974	0.854	5.54
College Grad	0.29	0.009	0.045	0.022	0.25
Black	–0.20	–0.012	–0.043	–0.038	0.59
Other Ethnic	0.57	0.036	0.126	0.117	1.01
Female	–0.20	–0.012	–0.042	–0.037	0.50
Married	–2.32	–0.113	–0.440	–0.329	4.52
T	0.83	0.044	–0.155	0.147	4.35
TSQR	–0.02	–0.008	–0.070	–0.026	3.86
Kicker	8.24	0.581	2.347	2.763	2.42
Kicker*T	–0.38	–0.005	–0.018	–0.016	1.30
Kicker*TSQR	0.006	0.001	0.005	0.004	0.96

costs of offsetting these effects using, for example, Selective Reenlistment Bonuses. Finally, the usage equations will, with modest adjustments, provide a more rational basis for estimating the costs of educational incentives in the budget.

Enlistment Bonuses versus ACF: An Application

A potential use of the results presented in this paper is to help the Army choose among alternative enlistment incentives. Both educational benefit kickers and enlistment bonuses attract recruits into the Army. Under what conditions is one to be preferred to the other? In the simple example below we compare the relative efficiency of kickers versus enlistment bonuses under a stylized set of assumptions, taking into consideration the effect of the enlistment incentive both on the supply of recruits and on the retention of those recruits over time. This exercise is intended to illustrate potential applications of the type of models estimated in this paper, not to

provide a definitive cost-effectiveness analysis of educational incentives.

Assume that the Army wants to increase the supply of higher quality recruits who enlist for three years in MOS 11B (infantry) by 10 percent, while holding the supply of all other recruits constant. It can do this by offering an educational benefit "kicker" under the ACF of about $12,000, or an enlistment bonus of approximately $3,000.[35] We calculate that the average cost per recruit of obtaining a 10 percent increase in supply is $1,300 for the educational benefit kicker and $3,000 for the enlistment bonus.[36] Hence, if obtaining a given increase in the supply of recruits is the goal, kickers would appear to be less costly.

However, our research has shown that educational benefit kickers have a negative effect on the first-term reenlistment rate, while bonuses are neutral.[37] This suggests that recruits offered educational incentives will provide fewer years of service to the Army than those induced to enlist by bonuses. Based on a three-year first term and a four-year second term, we calculate that a soldier receiving an enlistment bonus will supply 3.46 man-years of service over two terms, while a soldier receiving a kicker will supply only 3.29 man-years of service. Hence, a 5 percent increase in recruit supply, using an enlistment bonus, will provide roughly the same number of man-years of service as a 10 percent increase achieved through educational benefit kickers.

The total cost of obtaining a given number of years of service, then, will be determined by the number of soldiers that must be recruited and trained and the costs of recruiting and training. The somewhat higher turnover resulting from the lower retention of soldiers receiving educational benefit kickers may not be significant if recruiting and training costs are relatively low. Table 8.12 presents a cost comparison of kickers and enlistment bonuses assuming that the number recruited in each instance is sufficient to obtain the same number of years of service over a maximum of two terms of service (seven years).

As indicated in Table 8.12, increasing enlistments using an enlistment bonus is *slightly* less costly if the goal is to achieve a given number of years of service. Fewer recruits are required using an enlistment bonus because bonus recipients

Table 8.12
Bonus Versus Kicker: MOS 11B (Infantryman)
(Expected Years of Service Constant)

	Kicker	Bonus
Average Cost		
Recruiting	$1,300	$1,500
Training[a]	$8,356	$8,356
Total Recruits		
Number	110	105
Percent Increase (due to incentive)	10%	5%
Expected Years of Service		
Average	3.29	3.46
Total	363	363
Total Cost	$1,062,160	$1,034,880
Cost/year	$2,926	$2,850

[a]Training costs are from the Army Manpower Cost System (AMCOS).

have somewhat higher first-term reenlistment rates compared to kicker recipients.[38] If the goal is solely to obtain a given increase in enlistments, or if future years of service are heavily discounted, a kicker will be a less costly incentive.

Note that, for skills with high training costs, the higher turnover induced by kickers becomes even more costly. To illustrate the importance of training costs in the choice of incentives, consider the results of a similar analysis for MOS 5H (EW/SIGINT Morse Interceptor) in Table 8.13.

Because the cost of turnover, in the form of training costs, has risen, the disparity between educational benefits and bonuses increases.[39]

VIII. Summary

Since the early 1980's, the Army College Fund has been an important tool for attracting high-quality individuals into the enlisted force. At the same time, our understanding of both the retention effects and the costs of the ACF is limited compared

Table 8.13
Bonus Versus Kicker: MOS 05H
(EW/SIGINT Morse Interceptor)
(Expected Years of Service Constant)

	Kicker	Bonus
Average Cost		
Recruiting	$1,200	$1,200
Training[a]	$45,010	$45,010
Total Recruits		
Number	110	104
Percent Increase (due to incentive)	10%	4%
Expected Years of Service		
Average	3.46	3.67
Total	381	381
Total Cost	$5,083,100	$4,805,840
Cost/year	$13,341	$12,614

[a]Training costs are from the Army Manpower Cost System (AMCOS).

to our understanding of other recruiting incentives. Because education benefits are used by soldiers primarily after separation from the Army, only recently have data become available that allow a careful examination of cost and retention effects.

In this paper we use data on soldiers from the 1982 accession cohort to estimate models linking attrition, reenlistment, and educational benefits use to soldier characteristics, including eligibility for participation in the ACF. Holding constant characteristics suggested by a theory of attrition behavior, such as AFQT, military occupation, and race, we find no statistically significant difference in first-term attrition rates between soldiers who are eligible for ACF participation and those who are not. However, we do find that ACF-eligible soldiers are less likely to reenlist at the end of their first term, holding constant other factors that affect reenlistment decisions. The difference is 10 percentage points for soldiers with a two-year initial term

and 5 to 6 points for those initially enlisting for three or four years.

Not surprisingly, we find that usage of educational benefits among individuals separating from the Army is significantly higher for those eligible to participate in the ACF. We also find that usage varies with a soldier's AFQT, education at accession, and time since separation.

We use the retention and usage models in an illustrative calculation of the cost-effectiveness of the ACF as compared with the enlistment bonus. Although soldiers eligible for the ACF have lower expected man-years of service than those who are not eligible, educational benefits usage, and therefore ACF costs, are low enough that the ACF is not definitively more or less cost-effective than the bonus. These calculations, however, are very rough and a more careful study is clearly required.

Notes

1. The present value of costs is equal to outlays discounted back to the accession point at a nominal discount rate of 8.5 percent, the rate recommended by the DoD Board of Actuaries.

2. Note that $300 per month in 1976 dollars is equivalent to about $560 per month in 1988 dollars, or a total benefit over 45 months (in 1988 dollars) of about $25,200.

3. Enlistment bonuses, basic pay levels, the number of recruiters, and other resources affecting the supply of recruits declined at roughly the same time. Nevertheless, the replacement of the GI Bill with VEAP undoubtedly was responsible for part of the decline in supply. This does not mean, necessarily, that the Vietnam-era GI Bill was an efficient recruiting tool. The budget cost of the GI Bill was roughly $5 billion in FY 1976. If only 10 percent of that had been allocated to other recruiting resources, such as enlistment bonuses or recruiters, it is unlikely that the supply of recruits would have declined.

4. See Fernandez (1982) for a description of the test and an analysis of the results.

5. Super VEAP offered kickers of up to $6,000 to qualified recruits enlisting in selected skills.

6. The Congressional Budget Office has estimated a model linking benefit usage under the Vietnam-era GI Bill to soldier

characteristics. To our knowledge, the work has not been published.

7. One reason for this error is that military life has aspects of an "experience" good. The potential recruit cannot be sure how well he will like Army life until after he has actually experienced it.

8. Note that, among those potential recruits *who enter,* the error will have a positive expected value. On average, recruits who enter will find Army life less enjoyable than expected. This is because those who made errors in the other direction are less likely to have entered.

9. The cost of default is measured as a negative number algebraically.

10. This specification ignores the timing of the default. A more complete specification would consider the dynamic programming problem of whether to default now or at some future time less than contract completion. This specification would be straightforward, but tedious, and would not add any additional insights to the theory. Hence, for simplicity, it is ignored.

11. However, the choice of contract length may be correlated with the soldier's expectation of the net benefits of military life. Those who select short contracts may be "closer to the margin" and more likely to default. The self-selection aspects of contract length may tend to obscure the structural effect of the time remaining on the contract.

12. A well-known empirical result is that high school graduates tend to leave at much lower rates than non-high school graduates. The traditional interpretation is that earning a high school diploma serves as a screen for qualities like perseverance. The possession of a high school diploma signals this characteristic. The text suggests other, perhaps complementary, interpretations.

13. That is, if the soldier is willing to wait, his *ex ante* expectation of the benefits of Army life are likely to be greater. If, on average, expectations are correct, an individual who is willing to wait is less likely to break his contract.

14. On the other hand, if those who leave early can typically use the educational benefits they have earned, the incentive for contract completion is mitigated.

15. It is sometimes argued that the value of educational benefits includes the increase in the present value of future earnings that additional education produces. This is true only if the individual could not obtain the education without the educational benefits; that is, there are imperfections in the market for human capital. Typically, the value of the educational benefits is simply the present value of the subsidy to education that those benefits represent.

16. It may be argued that we would ideally like to measure only the structural effect of kickers on the reenlistment probability through the effect on relative benefits. However, if the policy to expand or contract educational benefits is always confounded by the self-selection aspects of kickers, the combined effect is more relevant for policy purposes.

17. Bonuses are allocated to skills where there are shortages. If shortages in certain skills are due to poor retention in those skills, and the factors generating that poor retention are not included in the model, the effect of reenlistment bonuses will be biased downward.

18. To the extent that individuals with higher aptitudes also have better civilian opportunities, the net effect of AFQT in a reduced form equation is indeterminate.

19. However, the effect on relative prices may be confounded with tastes in a manner similar to the reenlistment equation.

20. Our data set did not include ETS, or change in ETS. Hence, we could not use the more typical method of defining a reenlistment. ETS was computed based on entry date and initial obligation.

21. As will become clear later, we used this definition because we attempt to link the reenlistment equation with the usage equation to test for self-selectivity.

22. Inclusion of a variable (T) indicating the number of months between the time the member left the Army and the censoring point, as discussed in the previous section, is an attempt to adjust for any bias that this censoring may induce.

23. Major Thomas Daula graciously provided the program allowing us to do this.

24. We are not entirely convinced that the true error structure of the equations is independent. The variable used to identify the reenlistment equation—reenlistment bonuses—was only weakly significant. Moreover, our data consist of only one entry cohort. Greater variation in the data may result in the plausible finding of nonzero covariance. There are a number of other sources of possible sample selectivity that we did not test, such as the relationship between enlistment supply and usage, and that also await further research.

It is interesting to note that Antel, Hosek, and Peterson (1987) tested for and rejected a similar dependence between enlistment supply and attrition. They, too, had a sample consisting of a single-entry cohort. We speculate that such a dependency may be found in a sample that consists of several entry cohorts so that there is greater variation in the conditions at entry.

25. In these and subsequent tables, the effect of a variable is simulated with all other variables held at their means. For mutually exclusive dummy variables, such as education, the effect is simulated by changing the variable from zero to one with the other mutually exclusive dummy variables held at zero.

26. It is interesting to note that if the most recent record of the member's education is used in the analysis, rather than education at entry, a GED has a positive and significant effect on survival probability.

27. The occupational codes are:

OCC1	Electronic Equipment Repairers
OCC2	Communications and Intelligence Specialists
OCC3	Medical and Dental Specialists
OCC4	Other Technical and Allied Specialists
OCC5	Functional Support and Administration
OCC6	Electrical/Mechanical Equipment Repairers
OCC7	Craftsmen
OCC8	Service and Supply Handlers

28. An experiment wherein members were offered kickers only after they entered the Army would be necessary to distinguish the self-selection effects of educational incentives on reenlistment behavior from the effect that these benefits have on the relative attractiveness of reenlistment.

29. In our data, there are a small number of two-year recruits who are not eligible for $8,000 kickers, allowing us to separate the effects of enlistment contract length from the kickers. However, the separate effects of initial contract length and kicker are not sorted out with much precision for recruits with a two-year obligation.

30. The reenlistment rate is defined here as, of those who survive until at least three months of the expiration of the initial contract, the proportion who remain for at least three months beyond the expiration of the initial contract.

31. Because of the limitations of our sample, two-year enlistments were excluded. Two-year enlistees would be the only group with more than 36 months in which to use the benefits. Since two-year enlistees may use benefits more intensively than others, the effect of "T," the number of months eligible for usage, may be biased if this group is included, confusing the effect of T with the (possibly) higher usage intensity of two-year enlistees that may be independent of T.

32. The specification contains T^2 as well as T, allowing the effect of additional months on the probability of using the benefits and on the amount used to decline over time. According to the estimates, maximum usage occurs after about 29 months.

33. The effect of kickers is captured by the dummy variable indicating kicker eligibility. If this variable were dropped, the interaction term would increase in significance.

34. Our usage equation is estimated conditional on separating at ETS. It would be relatively easy to reestimate the equation using data on all accessions, not solely those who left at ETS. Usage predictions for the entry cohort could then be made directly from this equation.

35. Our estimates of the effect of both educational benefit kickers and enlistment bonuses on the supply of high-quality recruits is illustrative, although they are reasonable. Fernan-

dez (1982) estimated that $12,000 kickers increased the supply of high-quality (AFQT Category I–IIIA high school graduate) recruits by 9 percent relative to offering $6,000 kickers. In a previous study, Haggstrom (1979) estimated that $6,000 kickers did not have a statistically significant effect on the supply of high-quality recruits, though the point estimate of the effect was about 6 percent. Allowing for erosion due to inflation between FY 1981 and the present, attributing an increase in supply of about 10 percent is not unreasonable.

A $3,000 enlistment bonus will increase the supply of high-quality recruits by about 10 percent under the assumption that the pay elasticity of supply is about 1.0 and that the present value of first-term pay over a three-year contract is about $30,000.

36. The cost of the educational benefit kicker is the present value of usage outlays, estimated from our cost equations. We assume the costs are generated by a high school graduate who scores in the 80th percentile on the AFQT, discounted to the enlistment point at a rate of 8.5 percent. The probability of reenlisting rather than leaving to use the benefit is taken into account in computing the expected cost.

37. It is not unreasonable to expect that the reenlistment probability of those induced to enlist by an enlistment bonus is lower than ostensibly similar recruits who enter without such an inducement. Those entering without a bonus will, on average, be more committed (have a stronger "taste" for military service) than those entering with a bonus. However, we found no direct evidence of such an effect in our data. In any case, the bonus is "neutral" in the sense that its value does not depend on whether the member leaves the Army or reenlists. Hence, its effects, if any, should be small relative to the effects of educational benefits.

38. Note that the analysis contains several assumptions that are favorable to the evaluation of educational benefits. First, we compute expected years of service based on a maximum of only seven years. The disparity would increase if we considered the probability of a full 20-year career. Second, the estimates of the expected cost of the educational incentive assume that only those who leave at the first-term reenlistment point use the benefits. In-service use and use by those who stay

beyond the first term is ignored. We expected that this additional usage is small, however.

39. The cost of both the educational incentive and the enlistment bonus are computed as the budget cost to the government. A strict social accounting may result in different relative costs. First, a bonus is a transfer in general purchasing power from the taxpayer to the bonus recipient. For those who would have enlisted anyway, the bonus is pure "rent." Hence, for inframarginal recipients the bonus is a transfer payment and not a real cost to society—it has no allocative effect. Educational benefits, on the other hand, are a transfer of general purchasing power from the taxpayers to dollars that can be spent only on education. Educational benefit recipients who would have enlisted without the benefits may nevertheless spend their benefits on education. Since they may value a dollar's worth of education at less than a dollar (i.e., at less than what the benefit cost the taxpayer) it is not a pure transfer payment. Hence, the "rents" associated with a benefit "in-kind" (education) may have a real social cost.

On the other hand, if there are imperfections in the market that result in an underinvestment in education, the social cost of education subsidies such as the ACF may be less than the budget cost.

9

Factors Affecting Reenlistment in the Army Reserves: Evidence From the 1986 DoD Survey

Paul F. Hogan
Christine M. Villa

I. Introduction and Summary

The Selected Reserves in the Army and the other Services have become an increasingly important component of national defense in recent years. Their numbers have grown both in absolute terms and relative to the active component. For example, between FY 1981 and FY 1986, the number of men and women in the Army Selected Reserves has increased by about 146,000, or 24 percent.

Despite this already large increase, it is likely that budget pressure to substitute lower cost part-time manning (reserves) for more costly full-time manning (active) in some mission areas will continue. Considering their growing importance, relatively little is known about the potential supply of reservists. Regardless of one's views concerning the current levels and future expansion of the reserve component, it is clear that sound policy decisions will demand a better understanding of the supply of qualified people to the reserves, the factors

affecting supply, and the tools available to influence supply than currently exists.

Reserve reenlistment behavior, an important aspect of the overall supply of reserve manpower, is illustrative of the current state of our knowledge in this area. What qualifies as the conventional wisdom appears to be somewhat pessimistic for policy. The supply of reserves is relatively unresponsive to pay, within the likely range of variation, and is determined largely by institutional factors, such as the primary employer's policies toward reserve participation. The empirical results have been limited by the relatively poor data that have been available for the reserves, and by a largely undeveloped theoretical framework for analyzing reserve participation.

In this effort, we have attempted to expand the existing research base on reserve reenlistment behavior using a recently created data set—the 1986 DoD Reserve Component Survey. The survey itself was administered over the period of February to June, 1986. The Defense Manpower Data Center (DMDC) augmented the survey data with information from the military personnel files for all those who were sent the survey. Using the personnel files, DMDC followed each member who received a survey through September 1987 to determine if the member remained in the reserve components. Hence, we are able to match the member's survey responses with actual retention outcomes over this period.

Our retention analysis concentrated on enlisted members in the Army Reserves and National Guard in three experience categories: those with six or fewer years of service; those with seven, eight or nine years of service; and those with 10 or 11 years of service. It is limited to those who, at the time of the survey, had an enlistment contract that expired between the time of the survey and September 1987—the window over which we were able to track actual retention outcomes.

Our model of retention behavior is based on the Shishko-Rostker (1976) model of moonlighting behavior. According to the Shishko-Rostker model, individuals hold jobs in addition to their primary job because of constraints on hours of work in their primary job. At the constrained number of hours of work in the primary job, the individual will accept a second, part-time job

if the wage offered by the part-time position exceeds the individual's value of time at the constrained number of hours in his primary job. Participation in the Army Reserves or National Guard is one type of part-time employment. Factors affecting the decision to remain in the reserves, therefore, include the wage offered by the reserves, the wage in other moonlighting opportunities, and factors affecting the member's marginal value of time at the (constrained) hours of work in his primary job. Included as explanatory variables are the member's annual reserve wage, his civilian wage in his primary job,[1] family income, the spouse's wage, hours of work in the primary civilian job, and various institutional and demographic variables.

Overall, the results of the analysis are mixed. The reserve pay coefficient has the right sign and is statistically significant for members with six years or less of service. Reserve pay is statistically insignificant for enlisted members with between seven and nine years of service. The coefficient has the right sign and is statistically significant for those with 10 and 11 years of service.

For those with six years of service or less, our estimates suggest that a 10 percent increase in reserve pay results in about 1.3 percent increase in the retention rate for those at an ETS (expiration of term of service) point. This elasticity, about 0.13, is much smaller than measured pay elasticities of first term active duty personnel of about 1.5. However, the dollars involved are also much smaller. In terms of the absolute dollar effect, rather than elasticities, the results are similar. An additional \$100 of annual pay for first-term active duty soldiers implies about a 0.8 percent increase in the active duty retention rate. A \$100 increase in reserve pay would imply about a 0.7 percent increase in the retention rate for members of the Army Selected Reserves (Reserve and National Guard) with less than six years of service. For reserve members with 10 or 11 years of service, a 10 percent increase in pay results in about a 1.2 percent increase in the retention rate.

Reservists with six or fewer years of service and those with between seven and nine years who work more hours on average

in their primary civilian job are somewhat less likely to stay in the reserves, as theory suggests. The variable had the wrong, albeit insignificant, sign for members with between 10 and 11 years of service. None of the other economic variables, including family income, the spouse's wage, and a measure of the local unemployment rate, are statistically significant. In general, members of the Army Reserve had a significantly higher retention rate than members of the National Guard.

During the course of the analysis, however, a potential problem with the survey data was discovered that suggests caution should be exercised in interpreting these results. The response rates to the survey were low. Response rates for Army Reserve and Guard enlisted members with six or fewer years of service, seven through nine years of service, and 10 and 11 years of service were 44 percent, 53 percent, and 63 percent, respectively. More importantly, it appears that retention behavior was systematically correlated with whether or not the member responded to the survey. Not surprisingly, those who responded were more likely to reenlist than those who did not. A formal analysis of nonresponse bias was beyond the scope of this research. However, the differences in retention rates between respondents and nonrespondents are not small and are unlikely to be fully explained by differences in other observable characteristics. Caution should be exercised in making inferences concerning the retention behavior of the reserve population based on a sample of respondents. We unfortunately conclude that this study is not immune from the problems that have plagued other research efforts in the area of reserve retention—poor data.

The remainder of this paper is organized as follows. The institutional characteristics of the reserve forces, particularly those relevant to retention research, are reviewed in Section II. Section III contains an exposition of our model of reserve retention, based on the Shishko-Rostker model of moonlighting behavior. The data are discussed in Section IV, and the results are presented in Section V.

II. Institutional Framework

An understanding of the institutional characteristics and compensation system of the Army's Selected Reserves is a

crucial ingredient in developing a model of retention behavior. Because most researchers in the field know less about the Selected Reserves than the active forces, we review it in some detail.[2]

Salient institutional characteristics of the Selected Reserves that are important for modeling include the following:

- Selected Reserve participation is part-time.
- Reservists do not have the geographical mobility of full-time soldiers, so vacancies must be found in local units.
- Two categories of recruits may be distinguished—prior service and nonprior service.
- Prior-service personnel can vest their active duty service for retirement by participating in the Reserves.
- The reserve enlistment contract may be a less binding constraint than an active duty contract.
- The flexibility of the reservist's civilian employer is an important influence in recruiting and retention decisions.

Background

The reserve forces consist of units and individuals that can be ordered to active duty service upon presidential declaration of a national emergency.[3] As components of the reserve maintained in the highest state of readiness, Selected Reserve forces will be called first upon mobilization. The Army's Selected Reserve forces consist of men and women in organized units of the Army Reserves and National Guard and, in some instances, individuals who are not attached to a reserve unit per se.[4] The Army Reserve strength at the end of FY 1986 was about 309,700, whereas the strength of the National Guard was about 446,200. The typical soldier in the National Guard has somewhat more experience than his Army Reserve counterpart. In FY 1986, the average number of years of service of the enlisted force was 7.9 years in the Guard and 7.0 years in the Reserve.

The ability of the Army Selected Reserves to recruit and retain personnel in the 1980's has been good. In FY 1986,

actual reenlistments exceeded goal by 7,700 in the USAR and by about 4,000 in the ARNG.

Institutional Characteristics

The problem of recruiting and retaining people in the Selected Reserves is somewhat different from the problem in the active forces. An obvious and important difference is that service in the Selected Reserves is part-time and must permit the member sufficient latitude to pursue a full-time civilian career under normal peacetime conditions. The constraints and demands placed on the actual or potential reserve member by his full-time civilian employer will exert a major influence on his decision to enlist or to remain in the Selected Reserves.

Geographic Mobility. Recruiting and retaining people for the Selected Reserves presents geographical constraints not found in the active forces. If an individual wants to participate, a vacancy must be found in the local unit. If a member's full-time employer requests that he transfer to another city, the member is forced to end his relationship either with his current civilian employer or with his current reserve unit. If he separates from his unit and moves to another city, he may or may not find a vacancy in another reserve unit. Moreover, he may reaffiliate only after months have passed since his separation from the original unit. Simply accounting for separations presents a challenging data problem for force managers and analysts.

Prior and Nonprior Service. There are two distinct populations of recruits to the Selected Reserves: those who enter with no prior military service and those who affiliate with a Selected Reserve unit after separating from active duty. The distinction is likely to be of some analytical importance because the behavior and motivation of the two groups may differ significantly and systematically. Prior to the reinstitution of a volunteer force, approximately 80 percent of Selected Reserve accessions were nonprior service recruits—recruits without prior active duty experience. The proportion of prior to nonprior service accessions increased dramatically during the early years of the All-Volunteer Force. Currently, the proportion of prior and nonprior service recruits is about even in the

ARNG, while in the USAR prior service accessions account for about 60 percent of the total.

Service Obligations. Nonprior service recruits typically enlist in the Reserves for six years. Nonprior service recruits pursue initial training, which lasts from 4 to 12 months depending on skill, on a full-time basis after entering the Reserves. Reservists typically complete 48 drills per year and spend 14 days on active duty (exclusive of travel time) each year. This places a time demand on them of roughly one weekend per month (a member can complete four drills in a weekend) and two full weeks in the summer.

Though reservists enlist and reenlist for fixed contract lengths, just as active duty personnel do, the contracts do not appear to be as binding as active duty contracts. If the individual moves away from his unit, for example, he is usually relieved of his commitment.

Private Employers. The flexibility and attitude of the member's civilian employer in permitting the member to satisfy the demands of reserve membership is a key aspect of the individual's choice to join and remain in the Selected Reserves. The employer is required by law to allow the member time off to meet his reserve training commitment. The employer is not, however, required to pay the member for that time. Moreover, it is unlikely that any law can prevent an employer from discouraging participation in the Selected Reserves if the employer believes that such participation is unprofitable to him and should be discouraged.

The net financial return from attending two weeks of active duty training will depend on the employer's leave policy. The employer may offer (a) an additional two weeks of leave with full pay to attend training; (b) an additional two weeks of leave but pay equal to the difference between the individual reserve pay and his civilian pay; (c) two weeks of leave without pay; or (d) only the opportunity to use normal leave time. The results of a 1979 survey of reservists (Hawes, 1981) are reported in Table 9.1, and show that the most frequent employer response toward reservists is leave with no pay. More than one-third of employers had this policy.

Table 9.1
Employer Leave Policy Toward Reservists

Policy	Response (Percent)
Leave, no pay	35.7
Leave, difference in pay	25.7
Leave, with pay	22.2
Must use vacation	9.2
Reservists self-employed	7.1

Selected Reserve Compensation

Selected Reserve personnel share the same basic pay table as active duty members. Pay consists of one-thirtieth of one month's basic pay plus longevity for each drill. A selected reservist may complete and be paid for up to two drills per day. Hence, on a weekend of drills he may earn four days' pay. Reservists are paid at the same rate as active duty personnel of the same grade and longevity when called to active duty, including their annual two weeks of active duty training.

Burright et al. (1982) suggest that net reserve pay may differ significantly from gross reserve pay. First, the reservist must pay his own expenses when traveling to and from training drills. Second, as discussed in the previous section, the civilian employer's policy toward reservists' leave will determine whether the member enjoys two weeks of reserve duty at an implicit wage rate that is higher, about the same, or below his normal civilian wage.

In addition to basic pay, members of the Selected Reserves may receive retirement pay beginning at age 60 for nonregular military service. An individual must complete 20 years of "satisfactory Federal service" as a member of the armed forces. A year in which a member earns 50 retirement credit points constitutes a year of satisfactory service. One point is granted for each day of active duty or active duty training, and one point is earned for attendance at drills. Up to two points may be awarded for multiple drills attended in a day. Fifteen points are earned per year for simply being in the Selected Reserves.

Retirement pay is computed in a manner similar to active duty retirement pay, except that effective years of service for

retirement pay purposes are calculated by dividing the total accumulated points by 360. For example, if the member accumulates the minimum of 50 points per year for 20 years, his effective years of service would be 2.8, and his monthly retirement pay would be about 7 percent of monthly basic pay.[5] The opportunity to vest active duty service provides an incentive for prior service personnel to affiliate and remain in the Selected Reserves.

Basic pay and retirement pay are the major elements of compensation for the Selected Reserves. A targeted reenlistment bonus program began in FY 1978. A bonus of $900 was offered to those who reenlist for an additional three years, while an $1,800 bonus was offered to those who reenlisted for six years. In FY 1979, an enlistment bonus program, offering nonprior service recruits up to $2,000, was started. This was followed in FY 1981 by an affiliation bonus for prior service recruits.

Reservists are also offered educational benefits, exchange and commissary privileges while on extended active duty, and health and life insurance benefits. Members who enlist, reenlist, or extend for six years beyond a current obligation in the Selected Reserves are offered educational benefits of $5,040 under the New GI Bill begun in 1985. Before 1985, recruits to the Selected Reserves were offered a choice between an enlistment bonus of up to $2,000 or educational benefits of up to $4,000 for enlisting in certain shortage skills.

III. Reserve Retention: Theory and Application

This section reviews the existing theory of participation in the secondary labor market and its application to the decision to enlist and remain in the Selected Reserves. In the first part we present an economic theory of moonlighting and review some of the evidence regarding that theory from civilian labor markets. Next we derive a simple model of the reenlistment decision in the Selected Reserves from this theory. This forms the basis for the results we present in Section V. We also discuss complicating factors and review applied studies of retention in the Selected Reserves, and present some conclusions that may be drawn from the existing research.

Theory

The decision to enlist or reenlist in the Selected Reserves differs, in general, from a more typical occupational choice decision in that participation in the reserves is largely "part-time." The decision to enlist in the reserves may serve as a low-cost way to experience military life. During the initial period of active duty training, the member may decide whether he enjoys military life, and may choose to enter active duty permanently. More generally, however, the reserves offer a way to serve one's country while continuing to pursue civilian interests, to obtain additional income to supplement earnings from civilian employment, and to hedge against unemployment. For those with prior active duty service but less than a full career, reserve affiliation is a way to vest active duty service toward retirement that might otherwise be lost.

Though service in the reserves is part-time, it does impose demands upon the member's time. Satisfactory participation typically means that the member "drills" one weekend a month, and also that he serves two continuous weeks on active duty for training purposes. As noted in Section II, the conditions under which the employer grants the reservist the time necessary for participation are important determinants of the net financial rewards of service in the Selected Reserves.

The decision to remain in the reserves is undoubtedly a function of a plethora of factors, including patriotism, a spirit of adventure, a desire to be with people of similar backgrounds and interests, and others. The economic framework for analyzing the decision to enlist or reenlist in the Selected Reserves is the theory of moonlighting or participation in the secondary labor market. This framework was developed most rigorously by Shishko and Rostker (1976), and was applied by them both to the decision to moonlight in the civilian sector and to the decision to participate in the Selected Reserves. This framework implicitly holds these intangible factors constant, and concentrates on the effect of financial incentives on reserve participation. This does not mean that these factors are unimportant or irrelevant. Rather, the focus is on a set of incentives that can be used for policy purposes to affect the supply of reserves.

A Model of Moonlighting. Though the Shishko-Rostker model is the direct precursor of our approach, it has its foundation in the theory of the allocation of time and the household production function, as developed by Becker (1965), and the family or household utility maximization hypothesis, as in Mincer (1962). The key insight is that nonmarket time or "leisure" has value to the family in "home production"—productive activity that takes place outside the labor market. The obvious example of this is childcare. Moreover, the division of labor within the household will be rational, based upon comparative advantages of each member of the family in market and nonmarket productive activities. This foundation should offer valuable insights in understanding and explaining participation in the reserves.

The Shishko-Rostker model postulates a utility-maximizing individual who accepts a second job or "moonlighting" opportunity because of a constraint on the number of hours he may work for pay at his primary job. That is, at the hourly wage of his primary job, he would like to work more but is not offered that opportunity (at his current wage) by his primary employer.

In the simple set-up of the Shishko-Rostker model, the individual allocates his time to his primary job, leisure or home-production time, and a secondary job, to maximize a utility function with leisure or nonmarket time and goods and services produced in the marketplace as arguments. That is, his problem is to:

$$\max U(L,X) \tag{1}$$

subject to:

$$X = W_p L_p + W_s L_s + Y_n$$
$$T = L_p + L_s + L$$

where

- L is leisure or nonmarket time;
- X is a composite market good, defined so that the price is unity;
- W_p and W_s are the hourly wage rates in the primary and secondary job, respectively;

L_p and L_s are time spent in the primary and secondary job, respectively;

Y_n is nonlabor income; and

Y is pecuniary income defined as $W_pL_p+W_sL_s+Y_n$. Note that $Y=X$.

In addition, the constraint that $L_p=L_p*$ (hours of work in the primary job are fixed at L_p*) is imposed to motivate the model. In the Shishko-Rostker model, there must be a limit on the hours that the individual may work at either the primary job or the secondary job. Otherwise, the individual would allocate all his labor market time to the job with the higher wage. We will briefly explore an alternative motivation for moonlighting behavior based upon risk aversion below.

Solving for the first order conditions of (1), and totally differentiating to obtain the properties of this function, we can obtain the following propositions:

(a) As in standard labor supply theory, an increase in moonlighting wage will have an ambiguous effect on the supply of hours allocated to moonlighting, as long as leisure is a normal good. However, the effect on the decision to *participate* in the moonlighting market is unambiguously positive, because there is no income effect in this case.

(b) An increase in the wage offered by the primary job, W_p, will reduce the quantity of hours supplied to the secondary job, as long as leisure (nonmarket time) is a normal good.

(c) An increase in nonlabor income, Y_n, will reduce hours supplied to the moonlighting job, as long as leisure is a normal good.

(d) An increase in required hours in the primary job, L_p*, will reduce hours supplied to the moonlighting job if leisure is a normal good and if the primary wage is greater than the moonlighting wage.

This model of multiple job holding is important for understanding reserve behavior since over 93 percent of reservists hold primary jobs in the civilian sector. In particular, W_s is a significant policy variable for reserve participation. The theory implies that the pure substitution effect of a change in the secondary wage rate is positive. An increase in the wage makes

nonmarket time more costly, and more hours are worked, all other things being equal. Shishko and Rostker expressly test this pure substitution effect and confirm the theory: a higher secondary wage results in more hours worked on the secondary job. In addition, Shishko and Rostker's combined substitution and income effect resulting from a wage change is positive. This combined effect is confirmed by O'Connell (1972) but rejected by Hunt et al. (1985) who estimate a backward-bending moonlighting supply curve. Note that the effect of an increase in the moonlighting wage on the decision to participate in the moonlighting market is unambiguously positive.

An increase in the primary wage will reduce moonlighting hours if leisure is a superior good. This result is confirmed by both Shishko-Rostker and O'Connell. However, Hunt et al. estimate a significant positive coefficient. There is no explanation consistent with the theory for this result.

The theoretical effect of a change in L_p* depends in part on the relative magnitudes of W_s and W_p. Where W_p is less than W_s and leisure is superior, an increase in L_p means a decrease in L_s. Both Shishko-Rostker and O'Connell find negative effects for L_p; Hunt et al. do not include the variable in their model.

An increase in nonlabor income will reduce moonlighting hours if, as expected, individuals use their increased income to purchase more leisure. Hunt et al. estimate the effect of nonlabor income on hours through its effect on the reservation wage. The positive effect of nonlabor income on the reservation wage is translated to an implausible positive effect on moonlighting hours. Nonlabor income in other studies is insignificant.

The authors of all three studies agree that moonlighters are characterized by larger families. Children increase the value of the time that either spouse devotes to home production, but the value of the wife's time apparently increases by more than the husband's. Hence, increased family size apparently encourages specialization, with wives specializing in household production and husbands in market production. In addition, Shishko and Rostker find moonlighters to be younger than nonmoonlighters, and Hunt et al. find them to have higher

mortgage payments. Working wives decrease moonlighting hours.

A Simple Model of Reserve Reenlistment

Our problem, of course, is not to predict the number of hours an individual will spend moonlighting in the abstract, but to predict the probability that an individual part-time soldier will choose to reenlist in the Army Selected Reserves. In this section, we derive a simple economic model of reserve reenlistment behavior. In the subsequent section, we discuss the limitations of this model and, in particular, the failure to capture the institutional aspects of the reserve reenlistment decision.

Suppose that we could assume that the member was going to work hours in addition to those of his primary job, either in the civilian sector or by remaining in the Selected Reserves. Suppose, further, that we assume the individual can choose his additional hours of work in either sector, given the secondary wage offer in either state.

Then, consider the indirect utility function in which we have substituted the quantity of leisure and goods demanded—given income and the price of leisure—that maximize utility. The utility from state A, in which the member reenlists, and state B, in which the member leaves the reserves and accepts a second job in the civilian sector, are given by:

$$\text{State A (reenlist): } U\{L(W_{As},Y_A),X(W_{As},Y_A)\}$$

$$\text{State B (leave): } U\{L(W_{Bs},Y_B),X(W_{Bs},Y_B)\}$$

Substituting the constraint that X=Y, the reserve member will reenlist if:

$$U\{L(W_{As},Y_A),Y_A\} > U\{L(W_{Bs},Y_B),Y_B\} \tag{2}$$

Now, differentiate U(...) with respect to W_s, the secondary wage, and we can approximate U_A-U_B as:

$$\left[U_L\,(dL/dY)\frac{dY}{dW_s} + U_L\,(dL/dW_s) + U_Y\frac{dY}{dW_s}\right]dW_s$$

Divide through by U_Y, the marginal utility of income, and we have an approximation to the dollar amount of the welfare

increase or decrease from reenlisting in the reserves rather than leaving to accept a civilian moonlighting job.

$$(3) \quad \{[\, U_L/U_Y(\frac{dL}{dW_s} + \frac{dL}{dY}\frac{dY}{dW_s})] + \frac{dY}{dW_s}\} (W_{As} - W_{Bs}) \cong DR$$

In words, the first bracketed expression is an approximation to the dollar value of the difference in income that results from reenlisting at wage W_{As} rather than accepting a moonlighting job in the civilian sector, while the second bracketed expression is an approximation of the dollar equivalent value of the difference in leisure, or home production time, associated with the choice. This is simply the difference in "rent" from reenlisting rather than leaving, under the restrictive assumptions we have made. Call this measure "DR."

Now, assume that there are nonpecuniary differences between A and B, and they enter the utility function additively. These differences interact with an individual's tastes and with other unobservable random components to produce a dollar-equivalent value of the net difference in state A and B due to nonpecuniary factors. This difference, e_i, is not observable to the researcher, but is distributed according to $f(e_i)$, with cumulative distribution $F(e)$, among potential reservists at the reenlistment point. It is assumed to have a mean of zero and finite variance. The criterion for reenlistment for individual i becomes, reenlist if:

$$(4) \qquad DR_i + e_i > 0$$

The probability that an individual reenlists, then, is the probability that e_i exceeds the value of the index DR_i, or

$$(5) \qquad Pr(e_i > -DR_i) = 1 - F(-DR_i)$$

If F(.) can be approximated by a cumulative normal or logistic distribution, this relationship can be estimated as a probit or logit model, respectively. We can, in fact, obtain a measure of DR by estimating a moonlighting supply curve, similar to Shishko-Rostker. This can then be integrated to obtain our proximate measure of the change in rents, DR.

This model is similar to the active duty models. Typically, in the active duty reenlistment models, such as the Annualized Cost of Leaving model (see Hogan and Black, 1990), it is

assumed that leisure, L, is fixed at a constant amount, independent of the decision to reenlist. This is probably a satisfactory assumption in the active duty model. Onerously long hours, deployments, and sea duty can be captured empirically in such models by inclusion of variables representing time spent at sea or deployment. This simple model, however, is not likely to capture the relevant details of the reserve reenlistment decision.

Complications in the Application to Reserve Reenlistment

There are two interrelated issues: (1) Will the individual continue to participate in the secondary (moonlighting) labor market and (2) if so, will this participation continue to be with the Army Selected Reserves?

The problem is complicated by the nature of the Selected Reserves:

(1) The individual reservist cannot, in fact, choose his hours of participation in the reserves, given his reserve wage rate. He must, instead, accept the reserve wage and required drills as a package. Because of this institutional constraint, we cannot assume a nice tangency between the marginal value of time and the Selected Reserve wage rate, as suggested by the first order conditions. The analysis using the indirect utility function is vitiated if the reservist is not necessarily "on" his supply curve, or demand for leisure curve.

(2) It is not necessarily the case that the member will leave the reserves in order to accept a preferred secondary job offer in the civilian sector. He may, for example, choose not to moonlight. Hence, we must consider withdrawal from the secondary labor market as an alternative in the analysis.

We can adapt the decision framework in light of (1) and (2) as follows. We evaluate two alternative civilian states, B and B′. The first is the case we considered previously in which the reserve member leaves and accepts a moonlighting job in the civilian sector. In the second, the member also leaves, but withdraws from the secondary labor market. His value of

leisure is $L^{B'}$, presumably greater than L^{B}, and moonlighting income no longer appears as part of income.

In this setup the criterion is reenlist if:

$$(6) \qquad U\{L_A, W_{As}(T - L_A - L_{p*}) + W_pL_{p*} + Y_n)\} >$$
$$\max\ \{U(L_B, W_{Bs}(T - L_B - L_{p*}) + W_pL_{p*} + Y_n),$$
$$\{U(L_{B'}, W_pL_{p*} + Y_n)\}$$

That is, the member will reenlist if the value to him of reenlisting is greater than either the value of leaving and accepting a civilian moonlighting position or the value of simply leaving the reserves and withdrawing from the secondary labor market entirely. We can no longer assume that the member will be "on" his supply curve for part-time work. When participating in the reserves, he accepts a package of hours of work and wage. Further, should he enter the civilian sector, he may choose a "corner solution" of no hours of part time work. For these reasons, we must, at least implicitly, attempt to evaluate the reenlistment from a less convenient framework.

This setup suggests a random utility model with three choices. A multinomial conditional logit model, with the choice of reenlisting, leaving to moonlight in the civilian sector, and leaving but withdrawing from the secondary labor market entirely, would be one possible specification. However, in the data sets available, we observe only if the member leaves the reserves. We will not know if he moonlights in the civilian sector. A reduced form specification is:

$$(7) \quad \text{Prob (Reenlist)} = \text{Prob}\{a_0 + a_1[W_pL_{p*} + Y_n]$$
$$+ a_2W_{Bs} + a_3W_{As}L_{As} + XB + e > 0\}$$

where XB is a vector of individual characteristics, such as marital status, number of children, etc., and associated coefficients.

(1) We expect $a_1 < 0$ because leisure is assumed to be a normal good. The marginal value of leisure will increase with an increase in non-moonlighting income, reducing the probability that the member will moonlight in general, and reenlist in the reserves in particular.

(2) We expect $a_2 < 0$, of course, because W_{Bs} is the opportunity cost of reserve service rather than private sector moonlighting.

(3) Finally, $a_3 > 0$ requires no explanation.

We assume that the individual has made the optimal decisions, conditional upon being in either state A or B. As mentioned previously, this means for case A that the member accepts a combination of hours of work and wage, rather than adjusting optimally, given the wage. Note that, in this formulation, we implicitly hold the member's full-time job constant between the two states. This, however, does not mean that it does not affect his retention decision. If leisure is a normal good, we would expect that, other things being equal, the higher the member's wage in his full-time job, the higher is his marginal value of time and the less likely he is to continue part-time work.

Equation (7) can be estimated as either a probit or logit, depending upon the assumptions made concerning the error, e. We are estimating the conditional probability of leaving, the "hazard rate", and will include age and years of service variables to control for the censoring that has occurred up to that point. Our data set will consist of only a cross-section of observations on civilian earnings, family size, and so forth, that are available from the DoD Reserve Components Survey. We will then determine if the member reenlisted by searching through subsequent records, up to 18 months beyond the time of the DoD Survey. If these variables are largely unchanged between the time the member decided to enter the reserves and the time they are measured in the survey, one would expect that they would have less explanatory power than if there were changes. We can assume, however, that in our cross-sectional measurement of these variables, those members with above, average civilian earnings experienced a larger increase than those with below-average earnings. Hence, we can interpret the effect of cross-sectional differences between members in these variables as consisting both of cross-sectional level differences, and as relative increases and decreases in these variables experienced by the individual member. We do not, however, observe the actual wage for any individual.

Household's Retention Decision. The moonlighting model is motivated by assuming that the individual faces a constraint on the hours he may work in his primary job. At this constraint, the individual's marginal value of leisure (or home production) time is not only less than the wage rate at his primary job, it is also less than the wage in his best secondary employment opportunity. Hence, the individual chooses to moonlight.

Now, consider the same argument in the household or family context consisting of two adult members. The family's problem is to:

(8) $$\max U(L_m, L_f, X)$$

subject to:
$$X = W_{mp}L_p + W_{ms}L_s + W_f L_{fp} + Y_n$$
$$T_m = L_p + L_s + L_m$$
$$T_f = L_{fp} + L_f$$

where

L_m is the leisure or home production time of the spouse who is a reserve member;

L_f is the home production time of the nonmember spouse;

X is a composite of the goods and services that can be purchased in the market, as before;

T_m and T_f are the total amounts of time available to the member and nonmember spouses, respectively;

L_p and L_s represent time spent in the primary and secondary job, respectively, for the member spouse, while L_{fp} is time spent working the labor market for the nonmember spouse; and

W_{mp}, W_{ms}, and W_f are the wage rates of the member spouse in his or her primary and secondary job and the wage rate of the nonmember spouse, respectively.

We assume that the spouses are, at the margin, substitutes in home production, but not perfect substitutes. That means that if one spouse increases his or her allocation of time to the marketplace, the marginal value of leisure or home production time of the other spouse increases.

The first order conditions imply:

(9) $$(U_{Lm} / W_{ms}) = (U_{Lf} / W_f)$$

From these first order conditions, and the innocuous assumption that the member and nonmember spouse are substitutes in home production at the margin, it is clear that an increase in the wage rate of the nonmember spouse will induce a decrease in desired moonlighting hours of the member. It will do this for two reasons. First, the higher wage rate of the nonmember spouse will increase his or her hours of market work, raising the marginal value of home production (or leisure) time of the member, inducing him or her to reduce moonlighting hours. Second, leisure is assumed to be a normal good. The higher income will increase the demand for leisure of the family as a whole.

Consider a hypothetical example of the implications of the household approach, as it applies to the reserve reenlistment decision. Assume the member's spouse has just completed degree requirements at the time the member must decide whether to reenlist in the reserves. Presumably, this would mean a large increase in the nonmember spouse's market wage. The nonmember spouse would increase hours devoted to the labor market, and, presumably, reduce hours devoted to home production activities. This raises the marginal value of time spent in home production activities of the member. Without a significant increase in the reserve wage, he or she is more likely to leave the reserves and withdraw from the secondary labor market, increasing the time spent in home production activities.

Revising our reduced form from the previous section to incorporate the effect of spouse labor market behavior on reserve reenlistment, we have:

(10) $$\text{Prob (Reenlist)} = \text{Prob}\{ a_0 + a_1 [W_pL_{p*} + W_fL_{fp} + Y_n] + a_2W_{Bs} + a_3W_{As}L_{As} + a_4W_f + XB + e > 0 \}$$

As suggested above, we expect that $a_4 < 0$. Note that focus upon the family and home productivity as well as market productivity will allow us to interpret the effects of variables that affect home productivity, such as the presence of children, especially a young child, in a more coherent fashion.

Multiple Job Holding as Behavior Toward Risk. As we have noted, the motivation for holding multiple jobs in the Shishko-Rostker model is a constraint on the hours of work in the primary job. This is somewhat unsatisfying in that Shisko and Rostker never provide an economic rationale for this constraint. Hence, the theory may appear to be based upon an arbitrary assumption. While one avenue of research is to provide an economic rationale for the constraint on hours of work in the primary job, we instead explore an alternative motivation for multiple job holding based upon risk aversion. Moreover, this rationale for multiple job holding may provide some new insights into factors affecting reserve participation.

An individual is said to be risk averse if he would prefer a given income with certainty rather than an uncertain income that has the same expected value. Diminishing marginal utility of income is implied by risk aversion. That is, $U_{YY} < 0$. We assume that risk-averse individuals choose to allocate their time among competing pursuits, possibly including multiple jobs, to maximize expected utility, or:

$$\max E[U(X,Y)] \tag{11}$$

Assume that the individual may choose from among a number of alternative jobs, and that he may allocate a number of his working hours, T_j, to each job, which offers wage w_j. Further, assume that these jobs are risky, and that the probability that individual is able to work the number of hours he planned is p_j. Further, assume that the probabilities are not perfectly correlated. Under these conditions, it can be demonstrated that the individual may choose to hold more than one job. In essence, he diversifies the risk of his "human capital" portfolio by choosing to hold more than one job.

Risk diversification provides an explanation for multiple job holding that does not rely on arbitrary constraints on hours worked. The individual may be better off by reducing hours in job 1 and accepting some hours in job 2 even though the wage in 1 is greater than in 2, $w_1 > w_2$. The possibility of multiple job holding as behavior toward risk follows from the assumption of a nonzero probability of a layoff and the diminishing marginal utility of income.

The risk-aversion model of moonlighting suggests additional propositions concerning reserve participation. These, largely, do not contradict the implications of the Shishko-Rostker model and may be considered complementary. The following propositions and insights appear to follow from the simple risk-aversion model:

(1) Other things being equal, the individual is more likely to moonlight and therefore reenlist in the reserves the higher is the risk of layoff in his primary job.

(2) Since the probability of involuntary separation in the Selected Reserves is largely uncorrelated with unemployment in the civilian economy, we would expect a higher probability of reenlistment in the reserves during periods of high general unemployment, and we would expect higher reenlistment probabilities in sectors of the country that have greater cyclical unemployment risk in the civilian economy.

(3) Again, other things being equal, the member is less likely to moonlight and therefore reenlist in the reserves, if the independent sources of family income are greater.

(4) To the extent that participation in the reserves lowers the cost to the individual of returning to active duty service, an increase in the general or sectorial level of unemployment may increase the probability that the individual leaves the reserves and enters active duty. Proposition (2) must be modified if this is the case.

A test of this risk-aversion hypothesis would be to include a measure of the riskiness of the member's primary civilian job in the retention equation. Unfortunately, we do not have such a measure.

Applied Studies

The responsiveness of reserves to pay and bonuses is probably the single most interesting result from these studies for policy purposes. The Grissmer, Doering, and Sachar (1983) analysis of the 1978 SR Reenlistment Bonus Test data revealed that a $900 bonus for three years and a $1,800 bonus for six years increased the reenlistment rate from 38.4 percent to 40.6 percent. Also, the bonus increased the average length of reen-

listment term from 1.31 to 4.37 years and, after two years, 37.3 percent of bonus recipients were still honoring their contract versus 30.4 percent of the reenlistees who were not bonus recipients. The follow-up study, Grissmer and Hiller (1983), estimated that over seven years, 490 man-years would be gained for every group of 1,000 reservists offered the reenlistment bonus.

Some authors differentiate between net pay elasticities and gross pay elasticities, where the former includes the mean lost income from the civilian job as a result of reserve participation. Grissmer et al. (1985) found a net pay elasticity of .2 for the Army National Guard. Burright et al. estimated a net pay elasticity of .12 and a gross pay elasticity of .18 for the National Guard. Overall, the findings suggest that pay has only a slight effect on reserve retention. The elasticities are smaller than the moonlighting elasticity measured for civilian moonlighters.

Burright et al. also found that net reserve time, civilian wages, and hours worked in a civilian job have only slight effects on reserve retention. Respectively, the elasticities are –.01, –.21., and –.26. As for the other civilian work environment variables, there are few concrete results. The employer's attitude toward reserve duty is reported by the reservist, and therefore may compound several factors. When reservists have to use their own vacation time to attend summer camp, the proportional change in the reenlistment rate is –0.07. However, only 9 percent of the respondents indicated that they were in this situation and the aforementioned result is not statistically significant.

Conclusion

There have been few studies of the relationship between reserve compensation and reserve enlistments and reenlistment, and even fewer studies of reenlistment behavior in the Army Reserve. The previous research offers little insight as to the best methods to use in any future work, at least compared to the voluminous research available for active duty personnel. Much of the literature reviewed here was generated from the 1978 Selected Reserve Reenlistment Bonus Test. Several researchers, including Burright and Grissmer, have noted that

the Army Reserve data are not very good. Hence the conclusions based on these data may be somewhat suspect.

IV. Data

Our data come from a combination of two major sources. The first is the 1986 DoD Reserve Components Survey administered by DMDC for the Department of Defense from January through March, 1986. This survey contains data on the socioeconomic status of the reserve member, data on the characteristics of his full-time civilian job, and data concerning the member's family, the labor market behavior of his spouse, and other information that is not available from any other automated source.

The second source of data is the members' personnel files. Extracts from the personnel files for all members who were *sent* a survey were taken from the Reserve Components Common Personnel Data System (RCCPDS). This system is an extract of reserve personnel files obtained from the Services and maintained by DMDC. Data from RCCPDS were obtained for all those in the survey's sample. The surveys returned by respondents were matched to the RCCPDS data. In addition, extracts of the RCCPDS were added to the file at six-month intervals, through September, 1987, for both respondents and nonrespondents. These file extracts provide an objective measure of who stayed and who left over this period, and form the basis of the dependent variable in our analysis.

1986 Reserve Component Survey

The 1986 Reserve Component Survey consists of two parts. The Member Survey consists of a sample of about 121,000 officer and enlisted members of the Selected Reserves from all the Services. In addition, the 1986 Reserve Component Spouse Survey was sent to the spouses of all the married members in the Member Survey—a total of about 79,000 spouses. Our data were taken entirely from the Member Survey.

Our focus is on enlisted members in the Army Selected Reserves who had 11 or fewer years of service at the time of the survey, and who had a reenlistment decision ETS between the time of the survey and September 1987. The criteria for being included in the analysis sample are (1) the member was an

enlisted member of the Army Reserve or National Guard at the time of the survey; (2) the member had 11 or fewer years of service at the time of the survey, and had an ETS between the time of the survey and September 1987; and (3) the member responded to the survey. This resulted in the sample sizes shown in Table 9.2.

Table 9.2
Sample Sizes

	YOS ≤6	YOS 7–9	YOS 10–11
Sample size	2,104	696	656

Nonrespondents

The overall response rate for the Member Survey was about 65 percent. However, for enlisted members of the Army Selected Reserves, the response rate was less—about 50 percent. For the population of interest in our analysis, the response rate is smaller still. Table 9.3 shows the response rate for the relevant portions of the sample.

Table 9.3
Response Rate
Army Selected Reserves

	YOS ≤6	YOS 7–9	YOS 10–11
ETS	40%	49%	59%
Non-ETS	49	55	64

In Section V, we discuss some of the potential problems associated with the relatively high rate of nonresponse.

Implications of the Cross-Sectional Nature of the Data

Relevant data on reserve members come from one cross-sectional snapshot—their status at the time of the survey. Ideally, we would like longitudinal data in order to determine how the status of the member has *changed* since the time of his last enlistment or reenlistment decision. To understand the statistical implications of having only a single, cross-sectional snapshot, consider the following simple model that is statistically equivalent to the model we will attempt to estimate.

Assume that individual i will enlist or reenlist in the reserves at time t if:

$$X_{it}B > -e_i$$

where X is a vector of both individual attributes and the attributes of the reserve position and its alternatives, and B is a vector of coefficients. Assume that the individual enlists (or reenlists) at time t. Obviously, he enlists (reenlists) because the value of XB at time t exceeds e_i, where e_i is the unobservable (to the researcher) component of reenlistment behavior, (sometimes referred to as his "taste" for reserve service).

In our sample, we observe this individual at time t+6, for example. Let us assume, quite reasonably, that there is positive correlation between both $X_{i,t}$ and $X_{i,t+6}$ and the unobserved component, $e_{i,t}$ and $e_{i,t+6}$. However, we as researchers observe only the data from one cross-sectional snapshot. That is, we observe only $X_{i,t+6}$. Now, if there is positive correlation between both the X's in the two periods and the e's in the two periods, the coefficients on the X's will be systematically biased toward zero.

To see this, consider the case of a member who joined, but had an observable index, XB, that was significantly below average. That is, the reason he joined was because of unobservable factors. He had a large "taste" for military service, i.e., he had a large value for e_i. When we observe him, his relatively low value of XB would otherwise indicate that he would not reenlist. However, the selection process and the assumed positive correlation between both the X's and the e's between periods means that there is an induced negative correlation between the X's and e's after the initial selection point. In our sample, those for whom we observe low XB's will have a higher than average "taste" component, or unobservable propensity to reenlist. Hence, our estimated B's from this sample will be biased toward zero.

Once we have pointed out this potential bias, the next issue is how one should correct for it. Unfortunately, the correction is both very simple and impractical. We need longitudinal data. That is, we must track the individual through at least two decision points, measuring the X's at each, in order to eliminate this form of bias. Since we only have one cross-

section of X's for the sample, this is a potential bias we can only note as we present our results from the cross-sectional data set.

V. Results

Variables

The model of reserve reenlistment behavior we estimate is based directly on the model of moonlighting behavior presented in Section III. The variables likely to affect moonlighting behavior, as well as continued participation in the Selected Reserves, include the reserve wage, the wage offered in alternative moonlighting activities, full-time earnings and hours of work in the full-time job, household nonlabor income, spouse wage, and number of dependents.

Hours of work and number of dependents affect the marginal value of leisure or nonmarket time. Greater hours of work in the primary job and the presence of dependents increases the marginal value of leisure, reducing the probability of reenlistment. Similarly, leisure or nonmarket time is assumed to be a normal good. Hence, a higher family income, other things being equal, increases the marginal value of time and reduces the probability of reenlisting.

Reserve pay is a measure of the opportunity cost of leisure. It should have a positive effect on the probability of reenlistment. We do not measure other moonlighting opportunities directly. However, we do measure years of education of the member, and we measure the difference in the unemployment rate in the member's state between the year in which he entered the Selected Reserves and the year of his reenlistment decision. To the extent that these variables affect civilian moonlighting opportunities, we capture a civilian moonlighting wage in reduced form. The spouse wage, on the other hand, represents the cost to the household of the spouse devoting more hours to household production. Hence, a higher spouse wage should be associated with a reduced probability of reenlistment.

Definition of Variables. The following is a brief description of the economic variables included in the model:

- Reserve pay. This variable is an estimate of average weekly reserve pay. It consists of the following two

components: first, basic pay, calculated for each individual based on his grade and year of service at the time of the survey (based on 48 drills per year), and, second, pay during the member's two weeks of active duty training. This active duty pay is determined in two steps. First, an estimate of actual basic pay and allowances is made based on the member's rank, year of service, and dependency status at the time of the survey. Then this amount is adjusted according to the policy of the member's employer regarding the two weeks of active duty training, as reported by the member on the survey. We distinguish three cases:

(1) The member may be required to use his own vacation, or take leave without pay during this period. In this instance, the member's imputed civilian pay is subtracted from his active duty pay.

(2) The member's employer pays him the difference between his reserve pay and his regular civilian pay, if the latter exceeds the former. The member's imputed reserve pay is equal to his civilian pay over this two-week period.

(3) The civilian employer provides time off with full pay (additional vacation) to attend full-time training. In this instance, reserve pay is imputed to be equal to the member's military pay and allowances, plus his civilian pay.

Finally, some occupational specialties are eligible for reenlistment bonuses of $1,500 for reenlisting after completion of the first term of reserve service. These are included in the weekly measurement of reserve pay for the relevant skills.[6]

- Civilian wage. This is defined as annual earnings reported from the survey divided by weeks of work, also reported from the survey.
- Spouse wage. Defined similarly to the civilian wage for the member's spouse.
- Spouse employed full-time. An indicator variable equal to one if the spouse is employed full-time.

- Hours of work. Average hours of work per week in the member's full-time civilian job, as reported in the survey.
- Overtime hours. The average number of hours the member works "overtime" at his full-time civilian job.
- Unemployment rate. The state unemployment rate at the time of the survey, by age category.
- Family income. Total annual family income, reported from the survey.

Demographic variables may affect the member's potential earnings from civilian moonlighting activities, as well as his marginal value of time. They may also be correlated with his "taste" for participation in the Selected Reserves. Demographic variables in the model include:

- Number of dependents. Number of dependents of the member, including his spouse.
- Years of education. Number of years of education of the member.
- Marital status. This variable is defined as one if married, zero otherwise.
- Gender. Defined as one if the member is female, zero otherwise.
- Nonwhite. Defined as one if the member is not Caucasian, zero otherwise.
- Student. A variable equal to one if the member is a student, zero otherwise.
- Age. Member's age, in years, at the time of the survey.

Institutional variables—variables that are related to the structure of the Selected Reserves—are related to the conditions of service in the Selected Reserves, or to systematic differences in members' tastes for service in the Selected Reserves. "Institutional" variables included in some specifications are:

- Reserve. An indicator variable set equal to one if the member is in the Army Reserves, and zero if in the Army National Guard.

- Prior service. An indicator variable set equal to one if the member has prior active duty service, zero otherwise.
- Years credited to retirement. The number of "good" years credited toward retirement from the Selected Reserves.
- DoD occupational categories. Nine dummy variables indicating the DoD occupational category of the member's reserve skill.[7]
- ETS1. Member's expiration of term of service (ETS) was between June and September, 1986.
- ETS2. Member's ETS was between September 1986 and March 1987.
- ETS3. Member's ETS was between March and September 1987.[8]

Variable Means. Reenlistment equations were estimated separately for those with six years or fewer of service, those with between seven and nine years of service, and those with 10 or 11 years of service, who had an ETS date between the time of the survey and September 1987. The variable means presented in Table 9.4 are for those included in the reenlistment analysis.

Table 9.4
Variable Means

	YOS<6	YOS 7–9	YOS 10–11
Reserve Pay	38.2	44.4	47.7
Civilian Wage	354.8	399.0	443.1
Family Income	8,322.3	14,700.0	16,569.0
Hours of Work	40.4	41.6	42.1
Avg. Overtime	3.2	3.3	3.4
Years of Education	12.7	13.1	13.0
Married	0.44	0.58	0.63
Dependents	2.0	2.6	2.9
Army Reserve	0.32	0.34	0.36
Spouse Wage	91.7	142.7	143.2
Full-time Spouse	0.22	0.32	0.35
Female	0.11	0.09	0.005
Nonwhite	0.25	0.24	0.25

Table 9.4 (continued)

	YOS<6	YOS 7–9	YOS 10–11
Unemployment Rate	0.11	0.09	0.054
Student	0.10	0.06	0.05
Prior Service	0.40	0.67	0.64
Age	27.3	33.6	35.5
ETS1	0.10	0.09	0.07
ETS2	0.33	0.32	0.35
ETS3	0.32	0.32	0.35

Estimation

The dependent variable is the probability the Selected Reserve member reenlists. Define net value or utility of reenlisting in the reserves for individual i as

(12) $$U_i = X_iB + e_i$$

as the net utility of reenlisting in the reserves, rather than leaving. X is a vector of the observable component of the characteristics of the reserves, alternatives to the reserves, and the individual, and B is a vector of coefficients to be estimated. The variable e_i is the unobservable component of this net utility index. The member is assumed to reenlist in the reserves if

(13) $$U_i = X_iB + e_i > 0$$
$$\text{or, } -X_iB < e_i$$

Let "e" be distributed according to f(e). The probability of reenlisting is given by:

(14) $$\Pr(-X_iB < e_i) = \int_{-XB}^{\infty} f(e)de$$

Once we make the appropriate distribution assumption concerning f(e) we can estimate model using maximum likelihood techniques. Let y=1 if the member reenlists and y=0 if the member leaves the reserves. If the cumulative distribution of f(e) can be described as a logistic curve, the likelihood function is given as

$$\Pi_{y=1}\, 1/(1+e^{-XB})\ \Pi_{y=0}\,[1 - 1/(1+e^{-XB})]$$

Results

The logit model of reenlistment behavior in the Selected Reserves was estimated separately for those with six years of service or fewer at the time of the survey, those with between seven and nine years of service, and those with 10 or 11 years of service. The coefficients of the logit model, with t-ratios in parentheses, are displayed in Tables 9.5 to 9.7.

Table 9.5 presents the models estimated for reserve members making reenlistment decisions between the time of the survey and September 1987 who had six or fewer years of service at the time of the survey. Reserve pay has the right sign and is statistically significant in both models. The coefficient on reserve pay implies that a 10 percent increase in the reserve wage results in approximately a 1.3 percent increase in the reserve reenlistment rate. Of the other variables that are implied by the theory of moonlighting to affect reserve participation, only family income is significant. It has a positive effect on reserve reenlistments, however. To the extent that this variable measures nonlabor income, its predicted effect is negative, if leisure is a normal good.

Table 9.5
Logit Reenlistment Model
YOS Six or Fewer

	Model 1	Model 2
Intercept	1.17	1.08
	(3.3)	(2.6)
Reserve Pay	0.016	0.016
	(2.8)	(1.9)
Civilian Wage	0.00007	—
	(0.36)	
Family Income	0.00002	0.000007
	(2.3)	(1.3)
Hours of Work	0.004	–0.002
	(0.06)	(0.35)
Avg. Overtime	—	–0.05
		(1.5)
Years of Education	–0.047	—
	(1.4)	
Married	0.03	0.06
	(0.08)	(0.5)

Table 9.5 (continued)

	Model 1	Model 2
Dependents	0.13	0.08
	(2.6)	(1.5)
Army Reserve	0.43	0.35
	(3.3)	(2.7)
Spouse Wage	0.000004	—
	(0.02)	
Full-time Spouse	—	−0.16
		(1.04)
Female	0.12	0.17
	(0.6)	(0.86)
Nonwhite	−0.007	−0.007
	(0.05)	(0.06)
Unemployment Rate	0.17	—
	(0.86)	
Student	—	0.03
		(0.17)
Prior Service	—	0.29
		(2.2)
Age	—	.012
		(0.9)
ETS1	−0.71	−0.71
	(3.2)	(3.2)
ETS2	−0.94	−0.96
	(5.7)	(5.8)
ETS3	−1.13	−1.12
	(6.7)	(6.8)
DoD1	0.09	—
	(0.22)	
DoD2	−0.55	—
	(3.06)	
DoD3	0.30	—
	(1.18)	
DoD4	0.13	—
	(0.42)	
DoD6	0.25	—
	(1.5)	
DoD7	−0.06	—
	(0.25)	
DoD8	−0.27	—
	(0.9)	
DoD9	0.04	—
	(0.21)	

The number of dependents has a positive effect on reenlistment behavior in both models 1 and 2, and is statistically significant in model 1. One interpretation of this is that the presence of children increases the household value of nonmarket time, but that the reservist's spouse has a comparative advantage in childcare relative to market activity. Hence, an increase in family size results in increasing specialization by the member in market activities, and specialization of the spouse in home production. In model 2, both increases in average overtime hours by the member in his primary job, and full-time employment by the spouse reduces the member's reenlistment probability, consistent with a rational allocation of time.

Those who are members of the Army Reserve are significantly more likely to reenlist than members of the National Guard, as indicated by the coefficient on "Reserve" in both models 1 and 2. Members who have prior active duty service are also more likely to reenlist, as indicated by the coefficient on "prior service" in model 2.

Inspection of Table 9.6 reveals that the results are not as good for those with between seven and nine years of service at the time of the survey. Reserve pay is statistically insignificant in both models 1 and 2, and has the wrong sign. Hours of work in the primary civilian job has the predicted sign, however, and is statistically significant in model 1. Those in the Army Reserves are again revealed to have a higher probability of reenlisting than those in the Guard, other things being equal.

Table 9.6
Logit Reenlistment Model
YOS Seven–Nine

	Model 1	Model 2
Intercept	2.97 (2.7)	2.5 (2.8)
Reserve Pay	−0.0008 (0.07)	−0.007 (0.6)
Civilian Wage	0.0008 (0.35)	—
Family Income	0.000005 (2.3)	0.000001 (1.06)

Table 9.6 (continued)

	Model 1	Model 2
Hours of Work	–0.02 (2.0)	–0.013 (1.2)
Avg. Overtime	—	–0.08 (1.5)
Years of Education	0.01 (0.2)	—
Married	0.5 (1.07)	0.18 (0.8)
Dependents	–0.10 (1.3)	–0.09 (1.1)
Army Reserve	0.65 (2.5)	0.69 (2.7)
Spouse Wage	0.0004 (0.5)	—
Full-time Spouse	—	0.09 (0.35)
Female	–0.43 (0.43)	0.39 (0.93)
Nonwhite	0.034 (0.13)	0.033 (0.12)
Unemployment Rate	0.13 (0.3)	—
Student	—	0.53 (1.04)
Prior Service	—	–0.05 (0.2)
Age	—	.016 (0.9)
ETS1	–1.06 (2.6)	–1.06 (2.6)
ETS2	–0.84 (2.7)	–0.84 (2.7)
ETS3	–0.65 (2.0)	–0.65 (2.0)
DoD1	0.66 (0.6)	—
DoD2	–0.30 (0.9)	—

Table 9.6 (continued)

	Model 1	Model 2
DoD3	0.34	—
	(0.58)	
DoD4	0.43	—
	(0.7)	
DoD6	0.08	—
	(0.25)	
DoD7	–0.34	—
	(0.73)	
DoD8	–0.52	—
	(0.9)	
DoD9	6.5	—
	(0.06)	

Finally, the results in Table 9.7 indicate that reserve pay has almost as large an effect on the reenlistment probability of those with between 10 and 11 years of service as it does on those with six or fewer years of service. A 10 percent increase in reserve pay for this group results in about a 1.2 percent increase in the probability of reenlistment.

Table 9.7
Logit Reenlistment Model
YOS 10–11

	Model 1	Model 2
Intercept	1.9	1.8
	(2.1)	(2.8)
Reserve Pay	0.023	0.017
	(2.0)	(1.5)
Civilian Wage	0.0007	—
	(1.08)	
Family Income	–0.00001	0.000007
	(0.9)	(0.64)
Hours of Work	0.007	0.009
	(0.6)	(0.7)
Avg. Overtime	—	–0.04
		(0.6)
Years of Education	0.07	—
	(0.9)	
Married	0.3	0.5
	(0.5)	(1.7)

Table 9.7 (continued)

	Model 1	Model 2
Dependents	0.08	0.06
	(0.6)	(0.6)
Army Reserve	0.41	0.68
	(1.3)	(1.5)
Spouse Wage	0.0003	—
	(0.4)	
Full-time Spouse	—	0.55
		(1.6)
Female	−0.77	−1.02
	(1.8)	(2.33)
Nonwhite	0.23	0.14
	(0.6)	(0.5)
Unemployment Rate	0.21	—
	(0.4)	
Student	—	−0.73
		(1.5)
Prior Service	—	−0.34
		(1.1)
Age	—	0.016
		(0.7)
ETS1	−1.06	−1.09
	(2.0)	(2.1)
ETS2	−0.84	−1.04
	(2.7)	(2.8)
ETS3	−0.65	−0.72
	(2.0)	(1.9)
DoD1	1.25	—
	(1.2)	
DoD2	−0.64	—
	(1.4)	
DoD3	0.64	—
	(1.07)	
DoD4	−0.001	—
	(0.02)	
DoD6	0.63	—
	(1.4)	
DoD7	11.14	—
	(0.09)	

Table 9.7 (continued)

	Model 1	Model 2
DoD8	0.32 (0.4)	—
DoD9	11.1 (0.46)	—

Overall, the results are somewhat disappointing. The coefficient on reserve pay had the hypothesized sign and was statistically significant in two of the three reenlistment year groups. Moreover, the magnitude of the pay effects is consistent with that found in the literature. The effects of the remaining variables were mixed, however. Few were of the right sign or statistically significant. Note, too, that the effect of the ETS dummy variable suggests a possible selection bias in the sample. The negative coefficients on the ETS dummy variables indicate that, relative to the omitted group who had an ETS between the time of the survey and June 1986, those who had a later ETS were less likely to reenlist. One interpretaton is that those who intend to leave tend to do so prior to their ETS, so that those who are close to an ETS point are a self-selected sample. In the next section, we explore the possible reason—nonresponse bias—for the relatively poor results.

Nonresponse in the 1986 DoD Reserve Survey

The overall response rate for the 1986 DoD Survey for the Selected Reserve was about 65 percent. However, the response rate for members of the Army enlisted Selected Reserve components was much smaller—less than 50 percent. Moreover, the response rate for junior enlisted, the subject of our analysis, was smaller still.

The existence of a significant number of nonrespondents, per se, does not necessarily mean that inferences drawn from the respondents, or a sample of the respondents, are not valid for the population. However, when the probability of response is significantly correlated with other behavioral outcomes of interest, extra caution should be taken in drawing population inferences, especially concerning behavioral outcomes correlated with the probability of response.

We did not undertake a formal analysis of potential nonresponse bias in the 1986 survey. For a formal approach to the analysis of potential nonresponse bias, see Hogan and Goon (1988). However, the data reported in Table 9.8 suggest that respondents had a higher probability of reenlistment than nonrespondents.

The retention rates calculated in Table 9.8 are rates for those members who were in the Army Selected Reserves at the time of the survey and extend through September 1987. The retention rates for survey respondents are higher than those for nonrespondents and they are higher regardless of whether the reservist had an ETS point between the time of the survey and September 1987. Because retention appears to be systematically correlated with survey response, population inferences concerning factors affecting reenlistment in the reserves should drawn cautiously when based only on survey respondents.[9]

Table 9.8
Retention Rates
Respondent versus Nonrespondent

	Respondent		Nonrespondent	
	ETS	**Non-ETS**	**ETS**	**Non-ETS**
YOS ≤ 6	.832	.963	.629	.907
YOS 7–9	.880	.979	.733	.926
YOS 10–11	.944	.971	.753	.928

VI. Conclusion

Overall, our results are consistent with those of other econometric studies of reserve reenlistment behavior. For example, we find a first-term reserve pay elasticity of about 0.13, which is in the range of the 0.20 found by Grissmer et al. (1984). However, our purpose was not to duplicate the mixed successes of other researchers in the field but to improve upon them. We were not able to do this. We believe that the reasons for our very limited success are similar to those cited by other researchers. Because service in the reserves is not a full-time job upon which individuals depend for their livelihood, noneconomic factors, inherently more difficult to measure, are likely to play a larger role relative to economic factors in explaining reserve reenlistment behavior than in the active

duty case. Hence, data that help to control for these other influences, and sound measurement of the economic incentives themselves, are likely to be more important in obtaining solid estimates of reserve reenlistment models than for active duty reenlistment models.

There are two major problems with the data we used to estimate our reenlistment model. First, there appears to be a potentially serious nonresponse bias in the data upon which we base our estimates. Those who responded to the survey are more likely to reenlist than those who did not. A formal analysis of nonresponse bias was beyond the scope of this effort, but should be conducted if the data is again considered as a source for estimating a reserve reenlistment model.

Second, a longitudinal data set, where reserve members are tracked through at least two decision points, is necessary to obtain unbiased parameter estimates, if unobserved heterogeneity is at all important. One cross-sectional snapshot is not sufficient to account for unobservable factors affecting enlistment or reenlistment decisions that are likely to be correlated over time.

Notes

1. We do not observe the member's earnings opportunities in other types of part-time employment. The member's education level is included as an explanatory variable, and it may be interpreted as controlling for civilian moonlighting opportunities in reduced form. The member's full-time civilian wage is undoubtedly correlated with his civilian moonlighting opportunities, also.

2. David Grissmer, a leading authority on the reserves, has observed that the institutional details in modeling the reserve forces are even more important than for the active forces.

3. The President may call up to 100,000 Selected Reserves for active duty for a period not exceeding 90 days without declaring a national emergency.

4. The Selected Reserve consists mostly of members who train together and will be deployed as units. However, some individuals, called Individual Mobilization Augmentees, will fill individual positions in active units upon mobilization.

5. For those who entered after the effective date of the 1981 DoD Authorization Act, the retirement pay would be 7 percent of an average of basic pay over the last three years of service.

6. We had two sources for determining who was eligible for a bonus. The Office of the Chief of the Army Reserves (OCAR) provided us with bonus tables specifying the eligible skills. In addition, a survey question asked the member if he was going to be eligible for a bonus at reenlistment. Unfortunately, the correlation between the two sources was not high. We used the bonus tables provided by OCAR to impute bonus eligibility.

7. These categories follow the DoD Occupational Code manual.

8. Our sample includes those who had an ETS between the time of the survey and September 1987—the last month tracked.

9. If retention is systematically correlated with response to the survey because of factors that are not otherwise measured in the estimated retention equations, one or more coefficients in the retention equation may be biased. We cannot, however, infer that they are biased simply because of the gross correlation between response and retention. A more formal analysis, which is beyond the scope of this paper, would be necessary to confirm the potential bias. However, the degree to which the retention rates vary between respondents and nonrespondents make such a bias likely.

References

Altman, Stuart, and Robert Barro. "A Model of Officer Supply Under Draft and No Draft Conditions." In *Studies Prepared for the President's Commission on an All-Volunteer Armed Force.* Washington, DC: U.S. Government Printing Office, 1970.

Antel, John, James R. Hosek, and Christine E. Peterson. *Military Enlistment and Attrition: An Analysis of Decision Reversal.* R-3510-FMP. Santa Monica, CA: RAND Corporation, 1987.

Arguden, R. Yilmaz. *Personnel Management in the Military: Effects of Retirement Policies on the Retention of Personnel.* R-3342-AF. Santa Monica, CA: RAND Corporation, 1986.

Baldwin, Robert H., and Thomas V. Daula. "Army Recruit Attrition and Force Manning Costs: Methodology and Analysis." In R.G. Ehrenberg, ed. *Research in Labor Economics, 7.* Greenwich, CT: JAI Press, 1985a, 311–38.

Baldwin, Robert H., and Thomas V. Daula. "Modeling the Retention Behavior of First-Term Military Personnel: Methodological Issues and a Proposed Specification." In R. G. Ehrenberg, ed. *Research in Labor Economics, 7.* Greenwich, CT: JAI Press, 1985b, 339–63.

Becker, Gary S. "A Theory of the Allocation of Time." *The Economic Journal, 75,* September 1965, 495–517.

Berger, Mark C., and Barry T. Hirsch. "The Civilian Earnings Experience of Vietnam-Era Veterans." *Journal of Human Resources, 18,* Fall 1983, 455–79.

Berndt, Ernest, Bronwyn Hall, Robert Hall, and Jerry Hausman. "Estimation and Inference in Nonlinear Structural Models." *Annals of Economic and Social Measurement, 3,* 1974, 653–65.

Black, Matthew. *Personal Discount Rates: Estimates for the Military Population*. Arlington, VA: Systems Research and Applications Corporation, 1983.

Black, Matthew, Paul F. Hogan, and Stephen Sylwester. *Dynamic Model of Military Reenlistment Behavior*. Arlington, VA: Systems Research and Applications Corporation, 1987.

Black, Matthew, Robert Moffitt, and John Warner. "Reply to Comment by Glenn Gotz on 'The Dynamics of Job Separation: The Case of Federal Employees.'" *Journal of Applied Econometrics*, forthcoming.

Black, Matthew, John Warner, and Jim Arnold. *Retention of DoD Civilians*. Arlington, VA: Systems Research and Applications Corporation, 1985.

Borjas, George J. "Self-Selection and the Earnings of Immigrants." *American Economic Review, 77,* September 1987, 531–53.

Borjas, George J., and Sherwin Rosen. "Income Prospects and Job Mobility of Younger Men." In R.G. Ehrenberg, ed. *Research in Labor Economics, 3.* Greenwich, CT: JAI Press, 1980, 159–81.

Borjas, George J., and Finis Welch. "The Post-Service Earnings of Military Retirees." Unpublished manuscript. Santa Monica, CA: Unicon Research Corporation, November 1984.

Borjas, George J., and Finis Welch. "The Post-Service Earnings of Military Retirees." In C. L. Gilroy, ed. *Army Manpower Economics*. Boulder, CO: Westview Press, 1986, 295–313.

Brown, Charles. "Military Enlistments: What Can We Learn from Geographic Variation?" *American Economic Review, 75,* 1985, 228–34.

Brown, Charles. "Notes on the Post-Service Earnings History Files." Unpublished manuscript. Institute for Social Research, University of Michigan, July 1988.

Brown, Charles. "The Quality Dimension in Army Retention." Unpublished manuscript. Institute for Social Research, University of Michigan, April 1989.

Buddin, Richard. *Analysis of Early Military Attrition Behavior.* R-3069-MIL. Santa Monica, CA: RAND Corporation, 1984.

Buddin, Richard. *Trends in Attrition of High Quality Military Recruits.* R-3539-FMP. Santa Monica, CA: RAND Corporation, 1988.

Burright, Burke K., David W. Grissmer, and Zahava Doering. *A Model of Reeinlistment Decisions of Army National Guardsmen.* R-2866-MRAL. Santa Monica, CA: RAND Corporation, 1982.

Butler, J. S., and Robert Moffitt. "A Computationally Efficient Quadrature Procedure for the One-Factor Multinomial Probit Model." *Econometrica, 50,* May 1982, 761–4.

Butler, John Sibley. "Inequality in the Military: An Examination of Promotion Time for Black and White Enlisted Men." *American Sociological Review, 41,* October 1976, 807–18.

Card, David, and Daniel Sullivan. "Measuring the Effect of Subsidized Training Programs on Movements In and Out of Employment." *Econometrica, 56,* January 1988, 497–530.

Chipman, Mark. *Comparative Analysis of Enlisted Retirement Behavioral Models.* NPRDC-TN-80-1. San Diego, CA: Naval Personnel Research and Development Center, 1979.

Cooper, Richard V.L. *Military Manpower and the All-Volunteer Force.* R-1450-ARPA. Santa Monica, CA: RAND Corporation, 1977.

Cooper, Richard. V. L. *Military Retirees' and Separatees' Post-Service Earnings.* Washington, DC: Coopers and Lybrand, 1983.

Cox, D. R., and D. Oakes. *Analysis of Survival Data.* London: Chapman and Hall, 1984.

Crane, Jon R., and David A. Wise. "Military Service and Civilian Earnings of Youths." In D. A. Wise, ed. *Public Sector Payrolls.* Chicago: University of Chicago Press (National Bureau of Economic Research), 1987, 119–37.

Cylke, Stephen, Matthew Goldberg, Paul Hogan, and Lee Mairs. *Estimation of the Personal Discount Rate: Evidence from Military Career Decisions.* Professional Paper 356. Alexandria, VA: Center for Naval Analyses, 1982.

Cymrot, Donald J. *Early Attrition in FY 1985: The Effects of the Delayed Entry Program, Accession Month, and Enlistment Program.* CRM 86-192. Alexandria, VA: Center for Naval Analyses, 1986.

Dale, Charles, and Curtis Gilroy. "Determinants of Enlistments: A Macroeconomic Time-Series View." *Armed Forces and Society, 10,* Winter 1984, 192–210.

Danzon, Patricia Munch, and Lee A. Lillard. *The Resolution of Medical Malpractice Claims: Modeling the Bargaining Process.* R-2792-ICJ. Santa Monica, CA: RAND Corporation, 1982.

Daula, Thomas V. *The Retention of First Term Soldiers: Theory and Empirical Evidence.* Doctoral dissertation. Massachusetts Institute of Technology, 1981.

Daula, Thomas V. "Speed of Promotion, Military Pay, and the Reenlistment Decision." Paper presented at The Institute for Management Science/Operations Research Society of America Meetings, San Francisco, CA, May 1984.

Daula, Thomas V., and Robert H. Baldwin. "Reenlistment Decision Models: Implications for Policy Making." In C. L. Gilroy, ed. *Army Manpower Economics.* Boulder, CO: Westview Press, 1986, 203–21.

Daula, Thomas V., and Robert A. Moffitt. "A Dynamic Model of Enlisted Retention Behavior in the Army." Paper presented at the Army Research Institute/SRA, Inc. Conference on Army Compensation, April 1989.

Daula, Thomas V., and Roy Nord. *A Failure-Time Model of Recruit Quality and Soldier Performance.* Working Paper MPPRG 85-12. Washington, DC: U.S. Army Research Institute, 1985.

Daula, Thomas V., and D. Alton Smith. "Estimating Enlistment Models for the U.S. Army." In R. G. Ehrenberg, ed. *Research in Labor Economics, 7.* Greenwich, CT: JAI Press, 1985, 261–309.

Daula, Thomas V., and D. Alton Smith. "Recruiting Goals, Enlistment Supply, and Enlistments in the U.S. Army." In C. L. Gilroy, ed. *Army Manpower Economics.* Boulder, CO: Westview Press, 1986, 101–23.

DeTray, Dennis. "Veteran Status as a Screening Device." *American Economic Review, 72,* March 1982, 133–42.

DeVany, Arthur, and Thomas Saving. "Life Cycle Job Choice and the Demand and Supply of Entry Level Jobs: Some Evidence from the Air Force." *Review of Economics and Statistics, 64,* August 1982, 457–65.

Doeringer, Peter, and Michael Piore. *Internal Labor Markets and Manpower Analysis*. Lexington, MA: D.C. Heath and Company, 1971.

Eckstein, Zvi, and Kenneth Wolpin. "The Specification and Estimation of Dynamic Stochastic Discrete Choice Models—A Survey." *Journal of Human Resources, 24,* Fall 1989, 562–98.

Efron, B. "Bootstrap Methods: Another Look at the Jacknife." *Annals of Statistics, 7,* 1979, 1–26.

Ellwood, David, and David Wise. "Uncle Sam Wants You—Sometimes: Military Enlistments and the Youth Labor Market." In David Wise, ed. *Public Sector Payrolls.* Chicago: University of Chicago Press, 1987, 97–118.

Enns, John H. *The Effect of the Variable Reenlistment Bonus on Reenlistment Rates: Empirical Results for FY 1971.* R-1502-ARPA. Santa Monica, CA: RAND Corporation, 1975.

Enns, John H. *Reenlistment Bonuses and First Term Retention*. R-1935-ARPA. Santa Monica, CA: RAND Corporation, 1977.

Enns, John H., Gary R. Nelson, and John T. Warner. "Retention and Retirement: The Case of the U.S. Military." *Policy Sciences, 17,* 1984, 101–21.

Fernandez, Richard L. *Enlistment Effects and Policy Implications of the Educational Assistance Test Program*. R-2935-MRAL. Santa Monica, CA: RAND Corporation, 1982.

Fernandez, Richard, Glen Gotz, and Robert Bell. *The Dynamic Retention Model.* N-2141-MIL. Santa Monica, CA: RAND Corporation, 1985.

Fisher, Anthony. "The Cost of the Draft and the Cost of Ending the Draft." *American Economic Review, 59,* June 1969, 239–54.

Goldberg, Lawrence, and Peter Greenston. "Economic Analysis of Army Enlistments: Policy Implications." In C. L. Gilroy, ed. *Army Manpower Economics*. Boulder, CO: Westview Press, 1986, 61–94.

Goldberg, Matthew, and Dean Follmann. *Numerical Methods in Maximum Likelihood Estimation*. CRC-583. Alexandria, VA: Center for Naval Analyses, 1988.

Goldberg, Matthew S., and John T. Warner. *Determinants of Navy Reenlistment and Extension Rates*. CRC-476. Alexandria, VA: Center for Naval Analyses, 1982.

Goldberg, Matthew S., and John T. Warner. *Earnings of Military Veterans*. CRC-472. Alexandria, VA: Center for Naval Analyses, 1983.

Goldberg, Matthew S., and John T. Warner. "Military Experience, Civilian Experience and Earnings of Veterans." *Journal of Human Resources, 22,* Winter, 1987, 62–81.

Gotz, Glenn A. "Comment on 'The Dynamics of Job Separation: The Case of Federal Employees.' " *Journal of Applied Econometrics*, forthcoming.

Gotz, Glenn A., and John J. McCall. *Estimating Military Personnel Retention Rates: Theory and Statistical Method*. R-2541-AF. Santa Monica, CA: RAND Corporation, 1980.

Gotz, Glenn A., and John J. McCall. *A Dynamic Retention Model for Air Force Officers: Theory and Estimates. R-3028-AF.* Santa Monica, CA: RAND Corporation, 1984.

Grafton, Frances, and David Horne. *An Investigation of Alternatives for Setting Second-to-Third Tour Reenlistment Standards*. TR 690. Alexandria, VA: U.S. Army Research Institute, August 1985.

Grissmer, David W., Zahava Doering, and Jane Sachar. *The Design, Administration, and Evaluation of the 1978 Selected Reserve Reenlistment Bonus Test*. R-2865-MRAL. Santa Monica, CA: RAND Corporation, 1983.

Grissmer, David W., and John R. Hiller. *Follow-up of Participants in the 1978 Selected Reserve Reenlistment Bonus Test*. N-1880-MRAL. Santa Monica, CA: RAND Corporation, 1983.

Grissmer, David W., and Sheila Nataraj Kirby. *Attrition of Nonprior Service Reservists in the Army Reserve and National Guard*. R-3267-MRAL. Santa Monica, CA: RAND Corporation, 1985.

Grubert, Harry, and Rodney Weiher. "Navy Reenlistments: The Role of Pay and Draft Pressure." In *Studies Prepared for the President's Commission on an All-Volunteer Armed Force*. Washington, DC: U.S. Government Printing Office, 1970.

Haggstrom, Gus W., Thomas J. Blasche, Winston K. Chow, and William Lisowski. *The Multiple Option Recruiting Experiment*. R-2761-MRAL. Santa Monica, CA: RAND Corporation, 1981.

Hall, Robert E. "Importance of Lifetime Jobs in the U.S. Economy." *American Economic Review, 72,* September 1982, 716–24.

Hausman, Jerry A. "Military Compensation and Retention." Unpublished manuscript. Office of Economic and Manpower Analysis, United States Military Academy, 1984.

Hausman, Jerry A., and David A. Wise. "A Conditional Probit Model for Qualitative Choice: Discrete Decisions Recognizing Interdependence and Heterogeneous Preferences." *Econometrica, 46,* March 1978, 403–26.

Hausman, Jerry A., and David A. Wise. "Stratification on Endogenous Variables and Estimation: Gary Income Maintenance Experiment." In C. F. Manski and D. McFadden, eds. *Structural Analysis of Discrete Data with Economics Applications*. Cambridge, MA: MIT Press, 1981, 365–91.

Hawes, J. A. *1979 Reserve Force Studies Surveys: Description and Evaluation*. R-N-1750-MRAL. Santa Monica, CA: RAND Corporation, 1981.

Heckman, James, and Guilherme Sedlacek. "Heterogeneity, Aggregation, and Market Wage Functions: An Empirical Model of Self-Selection in the Labor Market." *Journal of Political Economy, 93,* December 1986, 1077–1125.

Heckman, James, and Burton Singer. "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data." *Econometrica, 52,* 1984, 271–320.

Hogan, Paul F. *An Economic Theory of First Term Attrition.* Washington, DC: Department of the Navy, 1979.

Hogan, Paul F. *Implied Personal Discount Rates of Military Personnel: Evidence from the Literature.* Washington, DC: Office of the Secretary of Defense, FM & P, 1982.

Hogan, Paul F. *ACOL 1.5: An Ad Hoc Method of Incorporating Multiple Horizons.* Washington, DC: Office of the Secretary of Defense, FM&P, 1985.

Hogan, Paul F., and Matthew Black. "Reenlistment Models: A Methodological Review," in *Military Compensation and Personnel Retention: Models and Evidence,* 1990.

Hogan, Paul F., and Marjorie Goon. *An Analysis of Potential Nonresponse Bias in a 1987 Air Force CATI Survey.* Arlington, VA: Systems Research and Applications Corporation, 1988.

Hogan, Paul F., and David K. Horne. *Military Retirement Accrual Charge as a Signal for Defense Resource Allocation.* TR 868. Alexandria, VA: U.S. Army Research Institute, 1990.

Hogan, Paul F., D. Alton Smith, and Stephen Sylwester. "The Army College Fund: Effects on Attrition, Reenlistment and Cost," in *Military Compensation and Personnel Retention: Models and Evidence,* 1990.

Horne, David K. "Modeling Army Enlistment Supply for the All-Volunteer Force." *Monthly Labor Review, 108,* August 1985, 35–9.

Hosek, James, and Christine Peterson. *Reenlistment Bonuses and Retention Behavior.* R-3199-MIL. Santa Monica, CA: RAND Corporation, 1985.

Hotz, V. J., and R. Miller. *Conditional Choice Probabilities and the Estimation of Dynamic Programming Models.* Unpublished manuscript. Carnegie-Mellon University, 1989.

Hunt, Janet C., C. R. Hill, and B. F. Kiker. "The Effect of Taxation on Labor Supply: The Case of Moonlighting." *Applied Economics, 17,* October 1985, 897–905.

Johnson, Kyle. "The Post-Service Earnings History File." Mimeographed. Arlington, VA: Defense Manpower Data Center, 1983.

Kalbfleisch, John D., and Ross L. Pretice. *The Statistical Analysis of Failure Time Data*. New York: John Wiley & Sons, 1980.

Lakhani, Hyder, and Curtis Gilroy. "Army Reenlistment and Extension Decisions by Occupation." In C. L. Gilroy, ed. *Army Manpower Economics*. Boulder, CO: Westview Press, 1986, 225–56.

Lancaster, Tony. "Econometric Methods for the Duration of Unemployment." *Econometrica, 47,* 1979, 939–56.

Lazear, Edward P. "Agency, Earnings Profiles, Productivity, and Hours Restrictions." *American Economic Review, 71*, September 1981, 606–20.

Little, Roger, and J. Eric Fredland. "Veteran's Status, Earnings and Race: Some Long Term Results." *Armed Forces and Society*, *5,* February 1979, 244–60.

Lucas, Robert. "Econometric Policy Evaluation: A Critique." In K. Brunner and A. Meltzer, eds. *The Phillips Curve and Labor Markets*. New York: North Holland, 1976, 19–46.

Manpower Requirements Report FY 1991. Washington, DC: Office of the Assistant Secretary of Defense, February 1990.

Martindale, Melanie, and Dudley L. Poston. "Variations in Veteran/Non-Veteran Earnings Patterns Among World War II, Korea, and Vietnam War Cohorts." *Armed Forces and Society*, *5*, February 1979, 219–43.

Mincer, Jacob. "Labor Force Participation of Married Women: A Study of Labor Supply." In H. G. Lewis, ed. *Aspects of Labor Economics*. Princeton, NJ: Princeton University Press, 1962, 63–105.

Nelson, Gary. "Economic Analysis of First Term Reenlistments in the Army." In *Studies Prepared for the President's Commission on an All-Volunteer Armed Force*. Washington, DC: U.S. Government Printing Office, 1970.

Nelson, Gary A. "The Supply and Quality of First-Term Enlistees under the All-Volunteer Force." In W. Bowman et al., eds. *The All Volunteer Force After a Decade: Retrospect and Prospect.* Washington, DC: Pergamon and Brassey, 1986, 23–51.

Nord, Roy D., and Edward J. Schmitz. *Assessing the Personal Discount Rate.* TR 673. Alexandria, VA: U.S. Army Research Institute, 1985.

Noznisky, Anne, Lori Ramsey, and Dianne D. Younkman. *Development of the Enlisted Panel Research Data Base.* RP 90-04. Alexandria, VA: U.S. Army Research Institute, 1990.

O'Connell, John F. "Multiple Job Holding and Marginal Tax Rates." *National Tax Journal, 32,* March 1979, 73–6.

Olsen, Randall J. "A Least Squares Correction for Selectivity Bias." *Econometrica, 48,* 1980, 1815–20.

Polich, J. Michael, James Dertouzos, and S. James Press. *The Enlistment Bonus Experiment.* R-3353-FMP. Santa Monica, CA: RAND Corporation, 1986.

Quandt, Richard, and Stephen Goldfeld. "GQOPT3/1." Mimeographed. Princeton University, 1984.

Rao, C. R. *Linear Statistical Interference and Its Applications.* New York: John Wiley and Sons, 1973.

Redner, R., and H. Walker. "Mixture Densities, Maximum Likelihood Estimation, and the EM Algorithm." *SIAM Review, 26,* April 1984, 195–237.

Report of The President's Commission on an All-Volunteer Force. Washington, DC: U.S. Government Printing Office, 1970.

Rodney, David, Cyrus Baghelai, Jacob Samanna, Michael Yaphe, and Paul Maletesta. *The Impact of Selective Reenlistment Bonuses Upon First and Second Term Retention.* Falls Church, VA: The Rehab Group, 1980.

Roll, C. Robert, and John T. Warner. "The Enlisted Career Manpower in the All-Volunteer Force." In W. Bowman et al., eds. *The All Volunteer Force After a Decade: Retrospect and Prospect.* Washington, DC: Pergamon and Brassey, 1986, 52–72.

Ross, Sue G., and John T. Warner. *Comparisons of Military and Veteran Compensation.* CRC-306. Alexandria, VA: Center for Naval Analyses, 1976.

Roy, A. D. "Some Thoughts on the Distribution of Earnings." *Oxford Economic Papers, 3,* June 1951, 135–46.

Sargent, Thomas. "Interpreting Economic Time Series." *Journal of Political Economy, 89,* 1981, 213–48.

Schmitz, Edward J. "The Retention Effects of Military Educational Benefits." Paper presented at the Institute for Management Science/Operations Research Society of America Meetings, Washington, DC, April 1988.

Schmitz, Edward J., Charles Dale, and Alan F. Drisko. "The Use of the Army College Fund: Implications for Program Cost Effectiveness." In T. R. Gulledge and L. A. Litteral, eds. *Cost Analysis Applications of Economics and Operations Research.* New York: Springer-Verlag, 1989, 407–22.

Shisko, Robert, and Bernard Rostker. "The Economics of Multiple Job Holding." *American Economic Review, 66,* June 1976, 298–303.

Slackman, Joel. *Quality Soldiers: Costs of Manning the Active Army.* Congressional Budget Office, June 1986.

Smith, Adam. *The Wealth of Nations.* New York: The Modern Library, 1937.

Smith, D. Alton, and Stephen Sylwester. *The Federal Retirement Decision: An Analysis of DoD Civilians.* Arlington, VA: Systems Research and Applications Corporation, 1988.

Smith, D. Alton, Stephen D. Sylwester, and M. Christine Villa. "Army Reenlistment Models," in *Military Compensation and Personnel Retention: Models and Evidence,* 1990.

Stafford, Frank P. "A Civilian Researcher's Guide to Army Recruitment and Retention of Enlisted Personnel." Unpublished manuscript. Institute for Social Research, University of Michigan, October 1987.

Tan, Hong W., and Michael P. Ward. *The Retention of High Quality Personnel in the U.S. Armed Forces.* R-3117-MIL. Santa Monica, CA: RAND Corporation, 1985.

Theil, Henri. *Principles of Econometrics.* New York: John Wiley and Sons, 1971.

Thomason, James. "Retention Costs of the GI Bill, the Draft, and In-Service Training: New Evidence from the Navy's

Enlisted Force." Working Paper 84-2047. Alexandria, VA: Center for Naval Analyses, 1985.

Ward, Michael, and Hong Tan. *The Retention of High-Quality Personnel in the U.S. Armed Forces.* R-3117-MIL. Santa Monica, CA: RAND Corporation, 1985.

Warner, John T. *Alternative Military Retirement Systems: Their Effects on Enlisted Retention*. CRC-376. Alexandria, VA: Center for Naval Analysis, 1979.

Warner, John T. *Military Compensation and Retention: An Analysis of Alternative Models and Simulation of a New Model.* CRC-436. Alexandria, VA: Center for Naval Analyses, 1981.

Warner, John T. *Determinants of Reenlistment and Extension Rates in the U.S. Marine Corps.* Memorandum 82-1733. Alexandria, VA: Center for Naval Analyses, 1982.

Warner, John T., and Matthew Goldberg. "Determinants of Navy First-Term Retention." Paper presented at the American Economics Association Meetings, Washington, DC, 1981.

Warner, John T., and Matthew S. Goldberg. "The Influence of Non-Pecuniary Factors on Labor Supply: The Case of Navy Enlisted Personnel." *Review of Economics and Statistics, 66*, 1984, 26–35.

Warner, John T., and Bruce Simon. *An Empirical Analysis of Pay and Navy Enlisted Retention in the AVF: Preliminary Results.* Memorandum 79-1878. Alexandria, VA: Center for Naval Analyses, 1979.

Warner, John T., and Gary Solon. "First-Term Attrition and Reenlistment in the U.S. Army," in *Military Compensation and Personnel Retention: Models and Evidence*, 1990.

Wilburn, Robert. "The Impact of Income, the Draft, and Other Factors on Retention of Air Force Enlisted Men." In *Studies Prepared for the President's Commission on an All-Volunteer Armed Force.* Washington, DC: U.S. Government Printing Office, 1970.

Zulli, David. *Zone C Recommitment Elasticity Estimates.* Santa Monica, CA: The Assessment Group, 1982.